UNIVERSITY OF CALGARY

Production Planning and Control for Flexible Interim Product Manufacturing in One-of-a-Kind Production

by

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Abstract

One-of-a-kind production (OKP) is generally complex flexible production which is characterized by discrete and non-numerical production decomposition, product design uncertainty and changes in resource availability. The old production management and control system, theory and methods do not handle this situation well because these technologies are developed with a view to time-invariant or static production state in the traditional large batch size manufacturing companies. Considering the manufacturing project (i.e. production planning and execution process) of OKPs as the main line of research, and by clarifying the optimal control and operational management of interim product production from a viewpoint of control system, we aim at analyzing the relationship between the control system actions and the crucial production indices that characterize working time expenditure, man hour cost and workforce consumption; and developing a closed-loop dynamic production cost control and optimization system of interim products based on working hours and manpower for OKP. The research involves the following aspects:

First: A method for workforce allocation and working time optimization problem with discrete and non-numerical constraints in OKP. With a top-down refinement method to specialize the product design and production decomposition in OKP, we suggest three unit task structures. For the typical double-level-nested parallel structure, according to analysis of complex industrial scenarios, a discrete-nested-set DP (dynamic programming) is presented to solve the workforce allocation and working time optimization problem.

Second: The optimal control methods based on MLHPP (the multilevel hierarchical PERT-Petri net) are proposed to analyze dynamic interim production cost control and
optimization under different workforce allocation and working time scenarios in a closed-loop control system.

Third: Entropy-weighted ANP fuzzy comprehensive evaluation of interim product production processes in OKP. OKP interim product production has the nature of multi-criteria production. To optimize the production processes influenced by complex factors, we establish an influence factor system and present a method that combines subjective and objective weights based on the entropy and an analytic network process (ANP).
Acknowledgements

I wish to thank my committee members who are more than generous with their expertise and precious time.
Dedication

I dedicate my dissertation work to my family. A special feeling of gratitude is given to my loving parents who have never left my side and are very special. I also dedicate this dissertation to my many friends and church family who have supported me throughout the process. I will always appreciate all they have done.
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<td>ANP</td>
<td>analytic network process</td>
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<tr>
<td>DES</td>
<td>discrete event simulation</td>
</tr>
<tr>
<td>FIFO</td>
<td>first in first out</td>
</tr>
<tr>
<td>JIT</td>
<td>just in time</td>
</tr>
<tr>
<td>LIFO</td>
<td>last come first out</td>
</tr>
<tr>
<td>MLHPP</td>
<td>multilevel hierarchical PERT-Petri net model</td>
</tr>
<tr>
<td>MRCGA</td>
<td>matrix real-coded genetic algorithm</td>
</tr>
<tr>
<td>OKP</td>
<td>one-of-a-kind production</td>
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<tr>
<td>PERT</td>
<td>program evaluation and review technique</td>
</tr>
<tr>
<td>PPS</td>
<td>product production structure</td>
</tr>
<tr>
<td>RS</td>
<td>random service</td>
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<tr>
<td>TOPNs-CS</td>
<td>temporized object-oriented Petri nets with changeable structure</td>
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<td>WBS</td>
<td>work breakdown structure</td>
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CHAPTER 1 INTRODUCTION

Production planning is the planning of production and manufacturing processes in a company or industry. It utilizes the resource allocation of activities of employees, materials and production capacity, in order to serve different customers (Fargher et al. 1996). Production planning is used in companies in several different industries. Different types of production methods have their own type of production planning. Production planning is a plan for the future production, in which the facilities needed are determined and arranged (Telsang 2006). For a specific time period, production planning includes the following periodically activities: determination of the required product mix and factory load to satisfy customer needs (Hung et al. 1996); matching the required level of production to the existing resources (Boucher 1987); scheduling and choosing the actual work to be started in the manufacturing facility (Fargher et al. 1996); setting up and delivering production orders to production facilities (Bertrand et al. 1999). Solberg (1981) presented that one of the key elements in successful production planning is the accurate estimation of the productive capacity of available resources, yet this is one of the most difficult tasks to perform well. Three production planning procedures that are material availability, resource availability and knowledge of future demand should be taken into account (Bertrand et al. 1999).

Production control is the activity of monitoring and controlling any particular production or operation. The American Production and Inventory Control Society (APICS) defined production control in 1959 as: production control is the task of predicting, planning and scheduling work, taking into account manpower, materials availability and other capacity restrictions, and cost so as to achieve proper quality and quantity at the time it is needed and then
following up the schedule to see that the plan is carried out, using whatever systems have proven satisfactory for the purpose.

Production planning and control is the combination of production planning and production control. In this thesis, the production planning & control problem and related key technologies in large-scale, one-of-a-kind production (OKP) flexible manufacturing are studied.

As a typical manufacturing paradigm, OKP presents various production management challenges and is controlled differently than is mass production. An OKP industry can be characterized by the following: (1) the industry’s product designs essentially change with every new order (Trostmann et al., 1993); (2) most of their customers’ orders contain one and only one product type (Trostmann et al., 1993); (3) most OKP products are produced only once, and although certain OKP products may be repeatedly produced, there is no fixed repetition period; (4) production stability is poor, and the production and process specialization degree are low. OKP is characterized by product design uncertainty and changes in resource availability (Jiang et al. 2001, 2003); In OKP, flexible interim production line is mainly used: i.e. productive resources (e.g. workforce, equipment) can be adjusted and changed according to actual production requirements; (5) most of the work requires multiple processes with discrete and non-numerical structures. (Here, non-numerical structure refers to a more natural model of data: e.g., the nested parallel structure can be regarded as the nested set of multiple discrete “graph” data structures, in which there is no operation sequence. A nested parallel task structure is three-dimensional: its space is defined by hierarchical structures and operation information); and finally, (6) the production automation level is low compared to non-OKP industries.

Physical examples of OKP industries can be easily found in heavy-equipment-type industries, e.g., shipbuilding, large electrical equipment building, heavy machinery building,
steel structure building, special equipment manufacturing and boiler manufacturing. OKP is generally complicated flexible production. We put emphasis on the study of OR (operations research) system considering time domain of OKP. In complex industrial production especially OKP, the old production management and control system, theory and methods, which focus on OR problems, do not handle this situation well because these technologies are developed with a view to time-invariant or static production state in the traditional manufacturing companies which are often mass production or large batch size manufacturing companies. In this sense, interdisciplinary efforts including OR, management science, industrial engineering and optimal control theory are needed to tackle the hard-nut topics in OKP.

The informatization and intellectualization in OKP has recently become a hot research topic. Research on efficiently carrying out specialized interim product production in OKP becomes one of the branches. In combination with the current situation of OKPs, we focus on flexible interim product manufacturing and intend to study control and optimization of working time and man-hour cost for interim product production. On this basis, production process optimization, and simulation technologies of production capacity and production planning are studied.

Taking the manufacturing project (i.e. production planning and execution process) as the main focus, and by clarifying unit structures of work tasks in the bottom level of the WBS (the work breakdown structure of interim production), we aim at developing a closed-loop dynamic production control and optimization system of interim products based on working hours & manpower for large-scale OKP. This research involves the following research questions:

First, in OKP, the problem of coordinating workforce allocations to obtain reasonable working time has practical significance. However, plenty of variables and complicated operation
relationships are involved, which implies the working time optimization in OKP belongs to a constrained mixed discrete optimization problem. In this thesis, to deal with the workforce allocation with the corresponding working time optimization in OKP (which often refers to complex production, e.g. shipbuilding), we introduce a top-down refinement method to specialize the product design and production decomposition in OKP, which also indicates the operation relationships of the interim product production processes. Consequently, we suggest three basic task structures which are with wide adaptability in OKP industry: tandem structure, parallel structure and double-level-nested parallel structure. Meanwhile, for the double-level-nested parallel structure, according to analysis of complex industrial scenarios, a discrete-nested-set DP (dynamic programming) is presented to solve the workforce allocation and working time optimization problem and the feasibility of this method is confirmed by calculation analysis of examples. Through the case studies, including an industrial implementation in the shipbuilding interim product (i.e. a hull block) production, our optimization method demonstrates significant potential to improve production efficiency.

Secondly, we address the closed-loop dynamic production cost control and optimization problem for interim products based on working hours and manpower for OKP. Although research on OKP control has been carried out for many decades, there is still a gap between research and application. OKP challenges real-time production dynamic control. The difficulty lies in two aspects. First, OKP is generally characterized by product design uncertainty and changes in resource availability. Second, specific types of OKP provide discrete production with complicated structures. The complicated work breakdown structure (WBS) of top-down & simple-to-complex refinement is introduced. Moreover, the production task relation structure in WBS, which consists of tandem structure, parallel structure and double-level-nested parallel
structure, is complex. Indeed, many OKP enterprises do not have an effective method to both control and plan adjustment for dealing with the progress of OKP operations under different workforce allocation and working time scenarios. We propose a cost dynamic control and optimization method based on the multilevel hierarchical PERT-Petri net (MLHPP) to achieve a closed-loop production dynamic control structure in OKP. Through a series of case studies, including an industrial implementation in shipbuilding interim production (e.g., a ship block building), we further verify the minimum cost model of our method, and show the solution is simple and practical.

The third research question addressed in this thesis is the problem of evaluating alternative interim product production schemes for OKP: an entropy-weighted ANP fuzzy comprehensive evaluation method is developed for this purpose. Most one-of-a-kind production (OKP) products are complex-shaped structural components, where there are only few identical OKP interim products in the same batch. OKP flexible interim product production has the nature of multi-criteria production; the multi-criteria production characteristics correspond to different manufacturing technologies and methods. To reasonably and efficiently determine group/batch production schemes of OKP interim products has become a key strategic consideration in OKP enterprises’ multi-criteria production decisions. The primary problem of the current multi-criteria evaluation method is how to judge the matrix scale and determine the weight set, which primarily depends on the rich experience of design and manufacturing engineers. These subjective decisions make the evaluation results prone to disagreements. To comprehensively and scientifically evaluate the production processes influenced by the complex factors in OKP, we establish an influence factor identification system and present a method that combines subjective and objective weights based on entropy and an analytic network process (ANP).
method avoids a multifarious optimizing process. In addition, this is a novel attempt to use fuzzy comprehensive evaluation based on ANP in production scheme optimization, which to an extent enriches process optimization methods in manufacturing. Through case studies, we demonstrate our methods feasibility and rationality. The improved evaluation result provides support for multi-criteria production decisions of interim products in OKP.

The remainder of this thesis is structured as follows. We begin with a review of the literature on OKP and production planning and control in Chapter 2. Each of the research questions noted in this chapter are then addressed in Chapters 3-6 respectively. The workforce allocation and working time optimization problem is addressed in Chapter 3 (Mei et al., 2016, DOI:10.1080/00207543.2015.1088972). We follow this with our work on production cost dynamic feedback control and optimization for interim products in Chapter 4. Chapter 5 (Mei et al., 2016, DOI:10.1016/j.cie.2016.08.016) focuses on entropy-weighted and ANP fuzzy comprehensive evaluation of interim product production schemes. The thesis concludes with a summary of this research and its contribution to production planning and control for OKP, as well as a description of ongoing and future work in this area.

In Chapter 3, thanks to Z. Zeng, he made contributions to algorithm analysis including convergence performance, sensitive analysis etc. for our nested-level task optimization model; thanks to other coauthors for critical revision of the work. In Chapter 5, thanks to coauthors for acquisition of data, and analysis and interpretation of results in the case study. In OKP manufacturing informatization and intellectualization field, with many collaborators’ assistance, I carried out this research and was responsible for major areas of concept formation and design, analysis and interpretation of data; and participated in drafting the article and revising it critically.
for important intellectual content etc. The MRCGA in appendix was developed by me for the specific application problem in Chapter 3.
CHAPTER 2 LITERATURE REVIEW

In this chapter we provide an overview of research relating to production planning and control for flexible product manufacturing in OKP. This chapter begins with a summary of recent work on OKP in Section 2.1; in Section 2.2, there is a review of the literature on production planning; and Section 2.3 focuses on the literature review on production control.

2.1 Literature review on OKP

Tu et al. (2000) reported a framework for computer-aided process planning (CAPP) in a virtual OKP process. Xie et al. (2005) investigated how to build an Internet-based, reconfigurable, rapid, one-of-a-kind or customized product development (ROKPD) platform and how to design appropriate intelligent tools and systems for the purpose of rapidly and economically producing OKP products in a global environment. Choi et al. (2006) presented an extensive performance analysis of dispatching rules for dynamic scheduling in OKP. Liu et al. (2008) addressed a dynamic capacitated production planning (CPP) problem for small- to medium-sized enterprises (SMEs): SMEs practise their businesses based on a manufacturing paradigm called OKP. Hong et al. (2008) addressed the issues in identifying an optimal product configuration and its parameters based on individual customer requirements in terms of performance and product cost. In addition, the research of Hong et al. (2010) presents a customer-centric product modeling scheme to model OKP product families by considering the relations between customer needs and OKP products. Luo et al. (2010, 2011) introduced a mathematical model for optimal operator allocation planning on a reconfigurable production line in an OKP process. A branch-and-bound algorithm with efficient pruning strategies was developed to solve this problem. Li et al. (2011) provided a comprehensive review of the recent developments of knowledge-based systems,
methods and tools for OKP. Aleksić et al. (2012) presented a case study that modeled the variations of a product configuration by examining the parameters and topologies in the mass production of custom windows and doors at an OKP company. Wang et al. (2012) introduced an easy-to-deploy and simple-to-use RFID-enabled manufacturing execution system (MES) to achieve real-time control for typical OKP workshops. Tietze et al. (2013) introduced a state-oriented approach for productivity measurement in OKP. With a case study, the authors show how to capture, visualize and evaluate state data of an OKP.

In addition to the literature reviewed above, other related research papers are briefly summarized in the following:

Jiang et al. (2001) defined colored Petri nets with changeable structures (CPN-CS), which are effective in modeling an OKP system that is characterized by product design uncertainty and changes in resource availability. Furthermore, Jiang et al. (2003) propose an approach for simplifying temporized object-oriented Petri nets with a changeable structure model (TOPNs-CS) for OKP systems, which was demonstrated to be a feasible and promising approach for automatically constructing TOPNs-CS models of OKP systems. Wei Li et al. (2011) presented a state space (SS) heuristic that was integrated with a closed-loop feedback control structure to achieve adaptive production scheduling and control in an OKP process. Zhang et al. (2012) modeled a dynamic pricing strategy (DPS) and compared the DPS to a constant pricing strategy (CPS) in an OKP setting.

These studies defined OKP and formulated related issues in OKP; however, none of the papers has directly addressed low production automation level in OKP, i.e. most of work in large-scale OKP needs to be completed manually, using a human workforce. Starting from coordinating workforce allocations to get reasonable working time, our research aims at
analyzing the relationship between the control system actions and the crucial production indices that characterize working time expenditure, man hour cost and workforce consumption; and developing a closed-loop dynamic production cost control and optimization system of interim products based on working hours and manpower for OKP.

2.2 Literature review on production planning

Burbidge (1985) introduced some of his most cherished beliefs in the field of production planning and control, which includes simple material flow systems, flexible programming, period batch control and system theory. Song et al. (2002) presented the performance analysis and optimization of assemble-to-order systems with random lead times. Rajaram et al. (2002) studied product cycling with uncertain yields. As described by Rajaram et al. (2002), the authors formulate the dynamic product-cycling problem with yield uncertainty and buffer limits to determine how much product to produce at what time to minimize total expected switching, production, inventory storage, and back order costs. Balakrishnan et al. (2003) studied production planning with flexible product specifications. Pahl et al. (2005) studied production planning with load dependent lead times. Fu et al. (2006) studied inventory and production decisions for an assemble-to-order system with uncertain demand and limited assembly capacity. Gupta et al. (2007) studied capacity management for contract manufacturing. Bendoly et al. (2008) studied the role of operational interdependence and supervisory experience on management assessments of resource planning systems. Huh et al. (2010) studied optimal pricing and production planning for subscription-based products. Huang et al. (2011) studied integrated order selection and production scheduling under make-to-order strategy. Aouam et al. (2013) studied integrated production planning and order acceptance under uncertainty. As described by
Aouam et al. (2013), the aim of this research work is to formulate a model that integrates production planning and order acceptance decisions while taking into account demand uncertainty and capturing the effects of congestion. Gong et al. (2013) studied optimal production planning with emission trading. Shi et al. (2014) studied production planning and pricing policy in a make-to-stock system with uncertain demand subject to machine breakdowns. Xiang et al. (2014) studied joint production and maintenance planning with machine deterioration and random yield. As introduced by Xiang et al. (2014), this integrated planning problem was formulated as a Markov decision process and analyse the structural properties of the optimal policies. Bilginer et al. (2014) studied production and sales planning in capacitated new product introductions. Manikas et al. (2015) discussed experiential exercises with four production planning and control systems. Aouam et al. (2015) proposed zero-order production planning models with stochastic demand and workload-dependent lead times. Khakdaman et al. (2015) studied tactical production planning in a hybrid Make-to-Stock – Make-to-Order environment under supply, process and demand uncertainties. Özer et al. (2015) studied integrating dynamic time-to-market, pricing, production and sales channel decisions. The authors study a firm’s time-to-market decision and subsequent sales channel, pricing and production decisions under three main sources of uncertainty. Bruecker et al. (2015) studied workforce planning incorporating skills: the research work presents a review and classification of the literature regarding workforce planning problems incorporating skills. As described by Bruecker et al. (2015): in many cases, technical research regarding workforce planning focuses very hard on the mathematical model and neglects the real life implications of the simplifications that were needed for the model to perform well; on the other hand, many managerial studies give an extensive description of the human implications of certain management decisions in particular.
cases, but fail to provide useful mathematical models to solve workforce planning problems. This review guided our research to find effective and efficient solutions regarding workforce planning problems.

In addition to the papers reviewed above, other related research papers on production planning with stochastic customer orders are briefly summarized in the following:


Although studies on production planning are extensive, research on useful mathematical models to solve workforce planning problems are still limited. Different workforce allocations directly affect optimal working time in manufacturing project especially OKP; the working time optimization and workforce allocations problem in complex OKP belongs to constrained mixed
discrete optimization problem, which is hard to be described as a unified mathematical model. Studies on workforce planning in OKP has practical significance, and our research focus on finding effective and efficient solutions regarding workforce planning problems.

2.3 Literature review on production control

Lu et al. (2005) studied production control framework for supply chain management. Li et al. (2006) studied production control in a two-stage system. Rubino et al. (2009) studied dynamic control of a make-to-order, parallel-server system with cancellations. Fredendall et al. (2010) studied the theory of workload control. According to Fredendall et al. (2010), some suggestions are made for future research that could increase the understanding of workload control rules and integrate this research with the understanding of lean production. Ohno (2011) studied the optimal control of just-in-time-based production and distribution systems and performance comparisons with optimized pull systems. Zhang et al. (2012) studied domain-based production configuration with constraint satisfaction. According to Zhang et al. (2012), a domain-based model is formulated to conceptualise the production configuration process, involving interconnections among multiple domains in conjunction with diverse domain decision variables and constraints. Karrer et al. (2012) studied a framework to engineer production control strategies and its application in electronics manufacturing. Lödding (2012) studied a manufacturing control model that links the tasks of manufacturing planning and control with the logistic objectives. Weng et al. (2012) studied control methods for dynamic time-based manufacturing under customized product lead times. Mehrgani et al. (2013) studied lockout/tagout and optimal production control policies in failure-prone non-homogenous transfer lines with passive redundancy. According to Mehrgani et al. (2013), the control problem is subject to non-negative
constraints on work-in-process (WIP), and the decision variables are the production rates of two main machines and a standby machine, and influence the WIP levels, the inventory levels and the system’s capacity, which is assumed to be described by a finite-state Markov chain. Kim et al. (2013) studied joint control of production, remanufacturing, and disposal activities in a hybrid manufacturing-remanufacturing system. According to Kim et al. (2013), the model was formulated as a Markov decision process, and the authors investigate the structure of the optimal policy that jointly controls production, remanufacturing, and disposal decisions. Wang et al. (2013) studied optimal production and admission control for a stochastic SOM system with demands for product and PSS. Olhager (2013) studied evolution of operations planning and control. In this research work, according to Olhager (2013), the authors take a historical perspective identifying the key trends and focus shifts in the evolution of planning and control, from shop floor control through material requirements planning (MRP), master production scheduling (MPS), and sales and operations planning (S&OP) to supply chain planning (SCP). Liu et al. (2013) studied a quality control method for complex product selective assembly processes. Feng et al. (2013) studied optimal control of production and remanufacturing for a recovery system with perishable items. Li-Chih Wang et al. (2013) studied distributed feedback control algorithm in an auction-based manufacturing planning and control system. According to Li-Chih Wang et al. (2013), most of the current manufacturing planning and control system (MPCSSs) that employ the centralised planning approach can have drawbacks, such as structural rigidity, difficulty in designing a control system, and lack of flexibility; therefore, this research aims to developing a closed-loop feedback simulation (CLFS) approach for adaptive control of the auction-based bidding sequence and may dynamically allocate production resources to operations. Bouslah et al. (2013) studied optimal production control policy in unreliable batch

Research of production control has been carried out for many decades, and the reports concerning production control in manufacturing in general are extensive. However, there is only a relatively small number of meaningful references that discuss dynamic production control in OKP incorporating complex hierarchical work breakdown structure, product design uncertainty and changes in resource availability. Even within these references, these studies either simply mention the topics or are indirectly related to our research. Regarding OKP interim product production as a production system, we put emphasis on simulating complex production processes
in OKP, and deal with the problem of finding a control law for a OKP system based on working hours & manpower such that a certain optimality criterion is achieved.
CHAPTER 3 A METHOD FOR WORKFORCE ALLOCATION AND WORKING TIME OPTIMIZATION WITH DISCRETE AND NON-NUMERICAL CONSTRAINTS IN OKP

3.1 Introduction

As a typical manufacturing paradigm, OKP presents various production management challenges and is controlled differently than is mass production. Generally, large-scale OKPs are complex flexible manufacturing, which implies the working time optimization in production processes not only relates to product composition parameters such as production schemes, workers of various sorts and different types of manufacturing equipment, but also to a great extent is affected by production process parameters. As discussed by Liu et al. (2005), these production process parameters such as structural relationships (e.g., as discussed in this chapter, a double-level-nested parallel task structure) and assembly sequences usually are discrete and non-numerical.

In OKP, differences among workforce allocations directly affect the working time which is not only the unit of cost measurement but also the important basis for reasonable enterprise planning and scheduling. Working time is defined as the start-finish duration of completing overall task. How to coordinate workforce allocations to achieve reasonable working time (i.e. use labor force efficiently) in OKP interim product production has practical significance.

According to the above analysis, the workforce allocation and working time optimization in large-scale OKP flexible manufacturing belongs to the constrained mixed discrete optimization problem, which is hard to describe as a unified mathematical optimization model.

We take the interim product production processes in OKP as the research unit of analysis, and define three basic task structures. The focus is on the workforce allocation with the corresponding working time optimization for a task with two-level-nested parallel structure that
is typical in large-scale OKP interim product production processes. A discrete-nested-set DP (dynamic programming) with matrix real-coded genetic algorithm (MRCGA) is proposed. For the nested-level, we use MRCGA to achieve optimized results of working time in different workforce allocation situations; thus, with decision variables from the nested-level, considering the nested-level as one stage of the main level, we apply DP to achieve the final optimized working time with relevant workforce allocation of the whole task. By using a shipbuilding company as a test bed, we validate that the production scheduling we proposed improves the company’s production efficiency in the hull block building tasks. Hence it provides the company significant flexibility and competitiveness. This work also lays a basis for presenting a closed-loop production control and optimization system based on working hours & manpower in OKP with the consideration of changeable production requirements that result from product design uncertainty and changes in resource availability.

Through literature review, none of the papers has directly addressed the detailed complex work task structure and its characteristics in large-scale OKP. In general, a top-down refinement method to specialize the product design and production decomposition in OKP, which also defines the task structures in OKP together with a method for solving the workforce allocation and working time optimization problem of complicated production tasks and processes are needed.

For solving this problem, difficulty lies in two aspects. First, differences among productive resources (e.g. workforce allocations) directly affect working time. Therefore, the optimization problem discussed in this paper is different from traditional machine scheduling problems. In OKP, the old production management and control system, theory and methods do not handle this situation well because these technologies are developed with a view to invariant
productive resources or static production state in the traditional manufacturing companies which are often mass production or large batch size manufacturing companies. Second, as mentioned above, in the double-level-nested parallel task structure, structural relationships and assembly sequences are discrete and non-numerical.

The rest of this chapter is organized as follows: Section 3.2 describes production scenario and defines three basic task structures in OKP. Section 3.3 presents a discrete-nested-set DP for solving the problem in the double-level-nested parallel task structure in OKP. Furthermore, Section 3.4 gives calculation analysis of examples and results from the case studies in a shipbuilding company. Finally, Section 3.5 draws conclusions and proposes future research.

### 3.2 OKP interim products and interim product production task classification

The Work Breakdown Structure (WBS) of an OKP is illustrated in Fig. 3-1 by Tu (1997).

![Figure 3-1. The design and production decomposition in OKP](image)

Based on Tu’s description, the design and production decomposition of OKP product is modeled in a three-dimensional space, i.e. time dimension (T axis), product design dimension
(Pd axis) and production specification dimension (Ps axis). Along the T axis, an OKP product is produced step by step and the production data become clearer due to the decomposition of production and design. Along the Pd axis, an OKP product design (from a general specification to detailed components) is continually improved or perfected. Along the Ps axis, production is specified or decomposed from a general requirement, or guideline into detailed processes.

To analyze the evolutionary and concurrent product development and production in OKP, the definition of an interim product needs to be given. An interim product in a WBS indicates a desired product state (e.g. a part) can be achieved from the starting product states (e.g. some components or raw materials). In OKP, the interim product is not only the operation unit of the production but also a component part of the working task decomposition for the final product. It is a component part in the stepwise formation of the final product. The interim products, for example, in shipbuilding include not only sub segments, parts and components but also outfitting pallet, module, unit and pipe fitting etc. OKP flexible manufacturing is very different from flow shops in batch and mass production. One of the main differences is all interim products in an OKP flexible production line are different, whereas the ones in batch and mass production flow shop are the same for a relatively large number of repetitions. In OKP, according to the similarity of operating or production processing, grouping various interim products into an interim product batch helps improve the efficiency of OKPs.

The essence of specialized interim product production in OKP is to group various interim products and establish a flexible production line of interim products. In this sense, it is important to analyze unitization structures of work tasks that comprise complex interrelated operations. When a manufacturing project is decomposed into a list of tasks through top-down refinement, i.e. a work breakdown structure, three unitization structures of work tasks are extracted: the
tandem structure (operations in a task are operated successively in chronological order, e.g., immediate predecessor-immediate successor operations); the parallel structure (operations are independent and do not have any relationships); nested parallel structure.

In practice, most interim product production processes are combinations of tasks with the three basic structures as mentioned above. Few interim products are produced with only one task structure. For the tandem task structure, network planning methods have been able to optimize the production planning according to the predecessor-successor relationship of operations. For the parallel structure, it could be solved by the traditional DP. For the multi-level-nested parallel structure, which can be regarded as the nested set of multiple discrete “graph” data structures, the working time optimization problem cannot be directly solved by related tools and software. However, in manufacturing assembly (or construction) industry especially OKPs like shipbuilding, this type of tasks occupies the largest proportion of the interim product production. Therefore our research work focuses on the optimization of the nested parallel tasks.

We discuss the workforce allocation and working time optimization method for the typical double-level-nested parallel task structure in OKP in Section 3.3.

3.3 Workforce allocation and working time optimization for double-level-nested parallel task structure in OKP

We propose a discrete-nested-set DP for workforce allocation and working time optimization problem of the double-level-nested parallel task in large-scale OKP.

3.3.1 Problem description and notation

The problem setting and notation are described as follows.
The main-level production task \( i \) consists of \( m \) operations and a nested-level task \( i' \). 1, 2, ... , and \( n \) parallel operations constitute nested-level task \( i' \), which means the nested-level task “includes” \( n \) independent operations. \( m \) operations in task \( i \) are also independent parallel operations in main-level task \( i \). There is no relationship between nested-level task \( i' \) and each independent operation in the main-level task \( i \).

Each operation’s required total man-hours (number of workers \( \times \) hour, a man-hour is the amount of work performed by the average worker in one hour.) is currently known and denoted as \( T_1, T_2, ... T_{n+m} \), which can be obtained from experience and is invariant.

The main-level task \( i \) is completed when all the operations in \( i \) are finished. The structural relationship between the nested-level task \( i' \) and its main-level task \( i \) is shown in Fig. 3-2.

![Diagram](image-url)

Figure 3-2. Nested-level task \( i' \) and its main-level task \( i \)
The main-level task $i$ is completed by $W$ group workers (in practical production process, the unit of workforce allocation is a “group”. Let one group = $g$ workers). The $i'$ is completed by $w$ groups of workers. Each operation of the main-level $i$ needs at least one group of workers to complete work. Also, the nested-level task $i'$ needs at least one group of workers. Here, $W \geq m+1$, $1 \leq w \leq W - m$, and $w \leq or > n$.

The optimization objective is to seek the minimum working time (or minimum start-finish duration) and relevant workforce allocation scheme when completing all independent parallel operations in the whole production task $i$.

The main-level task $i$ and the nested-level task $i'$ correspond to different production hierarchical levels, i.e. different analysis objects. Each operation in the main level carries state information (does not share production resources), whereas operations in the nested-level share task state as well as production resources. Moreover, according to production practice in OKP (e.g. hull construction, outfitting and painting in shipbuilding), each operation in the nested-level task can be further decomposed into subsets of an operation, which is similar to the relationship between process and thread in computer operating systems.

Scheduling problems in the nested-level have the following characteristics: (1) Stages of the problem are difficult to be determined, which indicates Bellman's principle of optimality is unable to be met; (Bellman’s principle of optimality: An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision.) (2) The state of each stage is time-dependent; (3) Recurrence relations for state transition are complex. Therefore, traditional DP is not suitable for solving this problem.
Genetic algorithm (GA) possesses advantages in parallel computing and real-coded GAs demonstrate to be ones of the most appropriate search methods on problems with large, complex, and poorly understood search spaces where continuous variables are implied (Herrera et al. 1998), so MRCGA is applied to solve the optimization problem in the nested level.

Based on the above problem description and notation, we make the following analysis of this optimization problem:

The objective: calculate the minimum working time (or minimum start-finish duration) with relevant workforce allocation.

The constraints: First, the parallel relationship of the operations means there is not any association among the operations; the start of each operation is independent and does not influence each other. Therefore, there is no operation sequence, which implies to make the sequence of decisions in accordance with certain conditions the optimal. Second, the double-level-nested parallel task structure is a nested set of multiple discrete “graph” data structures. Here, we regard each discrete node as graph data structure.

In large-scale OKP, the “double-level-nested parallel task” is the basic production unit of complicated production decomposition. Production processes in a flexible production line of interim products are combinations of tasks with the three basic structures as mentioned above. Based on practice in OKP, we make the following assumption:

**Assumption 1:** each of general workers with common technologies can operate the arbitrary operation in the production task.

Based on the above analysis and according to production characteristics of distinct hierarchical levels in OKP, a discrete-nested-set DP with matrix real-coded heuristic algorithm is
presented to solve the optimization problem of the double-level-nested parallel task structure in the following Section 3.3.2.

3.3.2 A solution method: the discrete-nested-set DP

In the double-level-nested parallel task structure, different workforce allocation schemes of the main-level task affect optimal working time of the nested-level task, while different optimal working time of the nested-level, in turn, has an influence on start-finish duration of the main-level task $i$.

The dynamic optimization process for achieving the minimum working time with the corresponding workforce allocation in a double-level-nested parallel task structure is indicated in the following Fig. 3-3.

![Dynamic Optimization Process Diagram](image)

**Figure 3-3.** The dynamic optimization process
The discrete-nested-set DP is indicated as follows:

Step variables: There are \( m + 1 \) phases in the whole process.

Decision variables: \( u_p \) is the number of the workforce units allocated to the \( p \)-th phase, \( p = 1, 2, \ldots, m + 1 \). Let the nested-level task \( i^* \) be the \((m + 1)-th\) phase.

State variables: \( c_p \) indicates the number of cumulative workforce units allocated to the phases from \( p \) to \( m + 1 \). Obviously, \( c_1 = W \) (\( W \) is the number of total workforce units), \( m - p + 2 \leq c_p \leq W - p + 1, p = 2, 3, \ldots, m + 1 \).

State transition equation: \( c_{p+1} = c_p - u_p \).

Set of admissible decisions: \( D_p(c_p) = \{u_p | 1 \leq u_p \leq \min(c_p, W - m)\} \), \( u_p \) is positive integer.

Step objective function: \( v_p(u_p) = \max\{T_p(u_p)\} \) shows the max time needed for completing the \( p-th \) operation with the allocated \( u_p \) workforce units.

Step objective function: \( v_p(u_p) = \max\{T_p(u_p)\} \) shows the max time needed for completing the \( p-th \) operation with the allocated \( u_p \) workforce units.

Optimal objective function: \( f_p(c_p) \) denotes the minimum time needed by \( c_p \) workforce units to complete the operations \( p, \ldots, m + 1 \) in all workforce allocation schemes.

The discrete nested-set DP equation is presented as follows:

\[
\begin{align*}
\left\{ f_p(x_p) &= \min_{u_p \in D_p(c_p)} \{\max\{T_p(u_p), f_{p+1}(c_p - u_p)\}\}; \quad p = m, \ldots, 1; \quad 1 \leq u_p \leq W - m \\
f_{m+1}(c_{m+1}) &= T_{m+1}(u_{m+1}); \quad u_{m+1} = c_{m+1}; \quad T_{m+1}(u_{m+1}) \leftarrow \text{fun}_\text{MRGCA}(u_{m+1}); \quad 1 \leq u_{m+1} \leq W - m
\end{align*}
\]

(3-1)
3.3.2.1 MRCGA function for the nested-level

The problem in the nested-level can be described as the allocation of \( w \) group workers in \( n \) parallel operations. There are various workforce allocation schemes for \( w \) group workers in \( n \) operations, meanwhile, the number of allocated worker group \( w \) is variable. For each \( w \) value, the optimization objective in the nested-level is to obtain the minimum working time for completing the parallel \( n \) operations in the task \( i^* \) according to different labor force allocation schemes. The optimization objective is \( t = \min\{\max(t_i)\} \), which will be further illustrated later in Equation (3-2). Here, \( t_i \) is the duration of \( i, i = 1,2,...,n \).

For the genetic algorithm application in the nested-level, the key is to use effective encoding and decoding methods and appropriate crossover and mutation operations.

*Individual encoding:* We utilize matrix real-coded method, and the chromosome code is:

\[
A_{s \times n} = \begin{pmatrix}
a_{11} & a_{12} & \cdots & a_{1n} \\
a_{21} & a_{22} & \cdots & a_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{s1} & a_{s2} & \cdots & a_{sn}
\end{pmatrix}
\]

Here, \( s \) denotes the number of stages when completing the task \( i^* \) (or count of workforce allocation); \( n \) denotes the number of operations in a task, \( a_{ij} \in [0,1] \). Each row in the matrix indicates the workforce allocation plan in a stage. In a row, the greater proportion means more allocated workforce. Using proposed coding, the MRCGA can simplify the follow-up total population initialization and the design of crossover and mutation operators without the constraint of the number of worker groups. MRCGA improves the search efficiency of GA, and further improves its performance. If it requires the exact number of worker groups to collaboratively carry out an operation in a task, \( a \) in the matrix can be defined when encoding.
**Population size selection:** A suitable population scale is important for genetic algorithm convergence. A small population scale makes it hard to get a satisfactory result. However, a large population scale increases too much computational complexity. According to past experience, the population scale is generally from 20 to 160.

Based on the above coding method, the corresponding crossover that we utilize is Parents-Gemini single point crossover (or simple crossover, Wright 1991; Michalewicz 1992) and the mutation is Gaussian. Population initialization, selection and reproduction are consistent with the general genetic algorithm. The algorithmic process consists of the following steps:

*Step 1:* Choose a coding for the problem, and give an initial population with \(N\) chromosomes. \(\text{pop}(1), t := 1\).

*Step 2:* Crossover probability is \(P_c\). After crossover, we obtain a new population with \(N\) chromosomes: \(\text{crosspop}(t+1)\). Then the old and new populations are combined into a large population.

*Step 3:* Fitness evaluation function. Since parallel operations are independent, there are various kinds of workforce allocation plans. For the optimization problem in the nested-level, we consider a complex case described as follows. Assume \(n\) parallel operations in the nested-level need \(S\) stages to be completed. Stage duration is \(t\). The lower limit of \(S\) is rounding up \(n/w\) to an integer; obviously, there is no upper limit. \(S\) is a simulation environment parameter.

Equation (3-2) calculates the total working time \(t\) of the \(n\) parallel operations in each stage. In Equations (3-2) and (3-3), \(T_i\) means the required total man-hours of operation \(i\), which can be obtained from experience. The fitness evaluation function \(f(t)\) is the reciprocal of stage duration \(t\).
\[
t = \max \left\{ \frac{T_i}{\sum_{s=1}^{i} (a_{si} \cdot w \cdot g)} \right\} \quad (i = 1, 2, \cdots, n) \tag{3-2}
\]

\[
f(t) = \frac{1}{t} \tag{3-3}
\]

In OKP, two or more workforce reallocations could further minimize working time. However, especially in the case where the number of total worker groups can satisfy the requirement of simultaneously performing all operations in a task, for example: in our case study \( w \geq n \), workforce allocation for multiple parallel operations normally happens only once because workforce allocation and adjustment are relatively cumbersome in practical production. In our case study, \( s = 1 \).

**Step 4:** Selection. Selection is utilized for restructuring or crossover operation. Its first step is to calculate the fitness values for selection. There are \( m \) individuals, and \( f_i \) is the fitness value of the individual \( i \). Therefore, for the individual \( i \), the probability of being selected \( p_i \) is as the following:

\[
p_i = \frac{f_i}{\sum_{k=1}^{m} f_k} \tag{3-4}
\]

and the cumulative probability \( p_j \) of the \( j \)th individual is

\[
p_j = \sum_{i=1}^{j} p_i \tag{3-5}
\]

Then we utilize roulette wheel selection. Multiple rounds of selection are needed for selecting the matching individuals. In each round of selection, there is a uniform random number from \([0,1]\). The random number is utilized to determine the individual candidates.
Step 5: Rule-bound mutation. With a smaller mutation probability $P_m$, we make a gene mutated in the chromosome: \( \text{mutpop}(t + 1) \); \( t := t + 1 \). So we obtain a new population: \( \text{pop}(t) = \text{mutpop}(t) \); then return to Step 2.

The whole algorithmic process is shown in Fig. 3-4.

![Algorithmic process diagram](image)

Figure 3-4. Matrix real-coded genetic algorithm process

3.3.2.2 Dynamic programming for the main-level

For nested-level parallel operations, we propose the matrix real-coded genetic algorithm to compute different values of optimized working time in the cases of different $w$ worker groups. The nested-level task $i^*$ is regarded as one phase of the main-level production task $i$. $i^*$ and the other independent main-level operations compose the main-level task $i$. The DP equation used to compute the minimum working time is based on the optimized results obtained from the nested-level. The method of computation is the typical backward induction.
Often in OKP, an operation among these $n+m$ operations needs two or more worker groups to complete it, i.e. it requires the exact number of worker groups to collaboratively carry out the operation and the required number of worker groups is specified on the operation sheet. Adding more workers to this operation does not reduce the processing time of the operation. In this case, the corresponding decision variables of DP can be specified for this type of operation.

3.4 Calculation analysis of examples and case study

In this section, calculation analysis of examples and results from the case study in a shipbuilding company are presented.

3.4.1 Calculation analysis of examples for the nested level

Calculation analysis of two examples for the nested level is indicated as follows. The population size is 100, the evolutionary times are 80, and the mutation probability is 0.3. The following optimized results are obtained by utilizing MATLAB R2015b.

Example 1: $n = 8$ ; $T_n = \{8, 4, 16, 10, 6, 24, 8, 12\}$, $n = 1, 2, \ldots, 8$ ; $w = 5$ ( $w < n$ ) ; $g = 3$ ; $S = 3$.

The optimal workforce allocation scheme is

$$
\begin{pmatrix}
1 & 1 & 0 & 1 & 0 & 0 & 1 & 1 \\
0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\
0 & 1 & 1 & 0 & 1 & 2 & 0 & 0
\end{pmatrix}
$$

The minimum duration of each stage is 2.6667 hours, i.e. $\min\{\max(t_i)\}$ of each stage. The total start-finish duration is $2.6667 \times 3 = 8.001$ hours.

Because $S$ is a simulation environment parameter with no upper limit, we further make the following analysis:
When $S = 4$, the optimal workforce allocation scheme is
\[
\begin{pmatrix}
0 & 1 & 1 & 0 & 0 & 2 & 0 & 1 \\
1 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\
1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\
\end{pmatrix},
\]
the minimum duration of each stage is 1.7778 hours. The total start-finish duration is $1.7778 \times 4 = 7.1112$ hours.

When $S = 6$, the optimal workforce allocation scheme is
\[
\begin{pmatrix}
0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 2 & 1 & 2 \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 & 1 & 0 & 1 \\
\end{pmatrix},
\]
the minimum duration of each stage is 1.1429 hours. The total start-finish duration is $1.1429 \times 6 = 6.8574$ hours.

When $S = 8$, the optimal workforce allocation scheme is
\[
\begin{pmatrix}
0 & 0 & 1 & 0 & 1 & 2 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 \\
1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 \\
0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 \\
0 & 0 & 0 & 1 & 0 & 1 & 1 & 2 \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 \\
\end{pmatrix},
\]
the minimum duration of each stage is 0.8889 hours. The total start-finish duration is $0.8889 \times 8 = 7.1112$ hours.
When $S = 10$, the optimal workforce allocation scheme is

\[
\begin{pmatrix}
0 & 0 & 0 & 1 & 0 & 2 & 0 & 2 \\
0 & 0 & 1 & 0 & 1 & 1 & 2 & 0 \\
1 & 0 & 0 & 1 & 1 & 1 & 1 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 \\
1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \\
1 & 1 & 1 & 0 & 0 & 1 & 1 & 0 \\
0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 1 & 0 & 0 & 2 & 0 & 1 \\
\end{pmatrix}
\]

the minimum duration of each stage is 0.6667 hours. The total start-finish duration is $0.6667 \times 10 = 6.667$ hours.

The relationship between simulation environment parameter $S$ (stages) and total finish time is illustrated in the following Fig. 3-5. With the increase of $S$ (stages), total finish time tends to decrease in general.

![Figure 3-5(a)](image-url)
Figure 3-5(b).

Figure 3-5. The relationship between $S$ and total start-finish time

Example 2: $n=10$; $T_n = 10 + \text{unidrnd}(20,1,ucN)$, $n = 1,2,\ldots,10$; $w=15$ ($w > n$); $g = 3$; $S = 4$.

The algorithm iterative process graph is as follows:

Figure 3-6. Algorithm iterative process graph
The optimal workforce allocation scheme is 
\[
\begin{pmatrix}
1 & 1 & 1 & 3 & 1 & 1 & 1 & 2 & 2 & 2 \\
2 & 3 & 2 & 1 & 1 & 1 & 1 & 2 & 1 \\
1 & 1 & 1 & 2 & 2 & 0 & 1 & 2 & 2 & 3 \\
3 & 2 & 0 & 1 & 2 & 1 & 1 & 1 & 2 & 2
\end{pmatrix}; \text{ the minimum duration of each stage is 1.3810 hours. The total start-finish duration is 1.3810\times4 hours.}
\]

3.4.2 Case study

In a shipyard, the construction of joining a batch of re-equipped “Swire Ship” blocks adopts “floating and sinking” method (i.e. a method for joining of hull sections in shipbuilding). Based on the research of this OKP production process, we utilize our method to optimize the working time of the ship block assembling tasks in the main production processes.

3.4.2.1 Case description

The Swire Series’ re-equipped ships are all container ships. The re-equipping plan is to cut off the original ship’s 81.5 rib position and embed the 28.305-meter-long parallel ship hull part, then to join the hull parts. It is demonstrated in Fig. 3-7. The refit project includes 15 larger items and 43 smaller items. The total additional weight is 860---950 tons. For improving the refit efficiency, it needs to optimize the working time of the whole ship refit project. The technical flow of “floating and sinking” method is shown in Fig. 3-8.
Figure 3-7. The construction of joining parallel hull’s parts

Figure 3-8. The technical flow of “floating and sinking” method
In the “Swire Ship” refitting and lengthening project, for the technological processes of “floating and sinking” cutting-off and overall closure, the main processes are: (1) the joining of new added amidships and the original rear ship block; (2) the total closure of the first block and new rear ship block. The implementation arrangements of the main processes are based on the experience. Our focus is the main processes’ working time control and optimization. The joining process (of the added amidships and the original rear ship block), for which workload counts for 60% of the entire ship refit jobs, is taken as test case to verify the optimization method based on MRCGA and DP.

For the main process, the required man-hours of each operation is illustrated in Table 3-1.

Table 3-1. The required man-hours of each operation

<table>
<thead>
<tr>
<th>Node</th>
<th>Task</th>
<th>operation</th>
<th>Total man-hours (number of workers × hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Join of the new added amidships and the original rear ship block (4)</td>
<td>Check the vertical positioning plate, check the closure position equipment (4-1)</td>
<td>4-1-1</td>
<td>3 (3*1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-2</td>
<td>9 (3*3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-3</td>
<td>6 (3*2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-4</td>
<td>12 (3*4)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-5-1</td>
<td>6 (3*2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-5-2</td>
<td>6 (3*2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-5-3</td>
<td>3 (3*1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-1-5-4</td>
<td>0.5 (fixed time)</td>
</tr>
<tr>
<td>Adjust the pressure burden to meet the upright floating (4-2)</td>
<td></td>
<td>4-2</td>
<td>20 (10*2)</td>
</tr>
<tr>
<td>Coarse positioning involution (the pumping process) (4-3)</td>
<td></td>
<td>4-3-1</td>
<td>10 (10*1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-3-2</td>
<td>20 (10*2)</td>
</tr>
</tbody>
</table>
Table 3-1. The required man-hours of each operation (continued)

<table>
<thead>
<tr>
<th>Node</th>
<th>Task</th>
<th>Operation</th>
<th>Total man-hours (number of workers × hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Join of the new added amidships and the original rear ship block (4)</td>
<td>Precise positioning (height difference 50mm) (4-4)</td>
<td>4-4</td>
<td>10 (10*1)</td>
</tr>
<tr>
<td></td>
<td>Install equipment to limit the position (4-5)</td>
<td>4-5</td>
<td>20 (10*2)</td>
</tr>
<tr>
<td></td>
<td>Pumping Tower Pier (4-6)</td>
<td>4-6</td>
<td>10 (10*1)</td>
</tr>
<tr>
<td></td>
<td>Check closure position test line, closure position assembly, welding (4-7)</td>
<td>4-7-1</td>
<td>3 (10*0.3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-7-2</td>
<td>20 (10*2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-7-3</td>
<td>20 (10*2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-7-4</td>
<td>120 (10*2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4-7-5</td>
<td>5 (10*0.5)</td>
</tr>
</tbody>
</table>

The relationship structure of tasks is described as follows:

![Diagram](image-url)

Figure 3-9. The relationship structure of tasks
3.4.2.2 Working time optimization of hull block assembling tasks

We have three steps to optimize the working time:

Step 1: Optimize the working time of the double-level-nested parallel task structure, which obtains the different optimized working time with relevant workforce allocation.

Step 2: Optimize the series connection tasks’ man time of the whole process.

The operations’ required man-hours in Table 3-1 are from the results of theoretical estimation based on experience. If there are disturbances in the production process such as bad weather, transportation and instrument damage, we expect that it is hard for the required production to be operated with strict accordance with this progress. Therefore, we have to consider work time utilization effectiveness when we plan a schedule. In the analysis of this case, we utilize the most optimistic time, the most likely time and the most pessimistic time to find the range of the production time that is in line with the actual situation of the shipyard production. Then we can get the mean value of the working period by the statistical method.

3.4.2.2.1 The working time optimization for double-level-nested parallel task:

We regard task 4-1 in the Table 3-1 as the study object to optimize the working time. The task includes eight operations. Among them, operations 4-1-1, 4-1-2, 4-1-3, 4-1-4 and 4-1-5 are independent operations. Task 4-1-5 is constituted by the independent tasks 4-1-5-1, 4-1-5-2, 4-1-5-3 and 4-1-5-4. The shipyard allocated 30 workers (10 worker groups) for task 4-1. The objective is to assign the worker groups reasonably and spend the shortest time (i.e. minimum start-finish duration) to complete parallel operations in the task.

Step 1: First, apply MRCGA to optimize the working time of tasks 4-1-5-1, 4-1-5-2, and 4-1-5-3. Compute the corresponding shortest duration with different workforce allocations. From
Table 3-1, we know the original data. The population size is 50, mutation probability is 0.3 and the evolutionary times are 50. The following optimal results in Table 3-2 are obtained by utilizing MATLAB R2015b. Since each operation needs at least one worker group, for task 4-1-5, the possible number of the allocated worker groups are 3, 4, 5 and 6.

Table 3-2. The optimized results of nested-level task

<table>
<thead>
<tr>
<th>Total number of allocated worker groups</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shortest duration (hour) &amp; workforce allocation plan</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>(1, 1)</td>
<td>(1, 2)</td>
<td>(1, 2)</td>
<td>(1, 3)</td>
<td></td>
</tr>
<tr>
<td>(2, 1)</td>
<td>(2, 1)</td>
<td>(2, 2)</td>
<td>(2, 2)</td>
<td></td>
</tr>
<tr>
<td>(3, 1)</td>
<td>(3, 1)</td>
<td>(3, 1)</td>
<td>(3, 1)</td>
<td></td>
</tr>
<tr>
<td>Remark</td>
<td>(X,Y), X indicates the operation; Y indicates the number of the allocated working groups</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For the realistic production in the case of $w > n$, the workforce allocation and adjustment are relatively cumbersome. Hence in the practical model of the task planning, we set $Step = 1$, which means there is at least one working group to operate each operation.

Second, we can obtain the different optimized working time when the different numbers of the working groups are allocated. Then we use DP to optimize the main-level’s five independent tasks, i.e. tasks 4-1-1, 4-1-2, 4-1-3, 4-1-4 and 4-1-5.

As shown in the following Table 3-3, taking task 4-1-5 as the fifth stage, we can get $t_p = t_p(u_p)$ of each stage.
Table 3-3. \( t_p = t_p(u_p) \) of each stage

<table>
<thead>
<tr>
<th>( u_p )</th>
<th>( t_1(u_1) )</th>
<th>( t_2(u_2) )</th>
<th>( t_3(u_3) )</th>
<th>( t_4(u_4) )</th>
<th>( t_5(u_5) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>---</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
<td>1.5</td>
<td>1</td>
<td>2</td>
<td>---</td>
</tr>
<tr>
<td>3</td>
<td>0.33</td>
<td>1</td>
<td>0.67</td>
<td>1.33</td>
<td>2.5</td>
</tr>
<tr>
<td>4</td>
<td>0.25</td>
<td>0.75</td>
<td>0.5</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td>5</td>
<td>0.2</td>
<td>0.6</td>
<td>0.4</td>
<td>0.8</td>
<td>1.5</td>
</tr>
<tr>
<td>6</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>1.5</td>
</tr>
</tbody>
</table>

When \( p = 5 \), \( f_5(u_5) = t_5(u_5) \), \( u_5 = c_5 \), \( 3 \leq c_5 \leq 6 \), we can obtain the following data:

\[
f_5(3) = 2.5, \ f_5(4) = 2.5, \ f_5(5) = 1.5, \ f_5(6) = 1.5.
\]

When \( p = 4 \), it can be obtained:

\[
f_4(x_4) = \min_{u_4 \in D_4(x_4)} \{ \max[t_4(x_4), f_4(x_4 - u_4)] \} \quad 4 \leq x_4 \leq 7, \ f_4(4) = 4, \ f_4(5) = 2.5, \ f_4(6) = 2.5, \ f_4(7) = 2.
\]

In a proper order, when \( p = 3 \), we can obtain: \( f_3(5) = 4, \ f_3(6) = 2.5, \ f_3(7) = 2.5, \ f_3(8) = 2 \). When \( p = 2 \), \( f_2(6) = 4, \ f_2(7) = 3, \ f_2(8) = 2.5 \). When \( p = 1 \),

\[
f_1(c_1) = \min_{u_1 \in D_1(c_1)} \{ \max[t_1(u_1), f_2(c_1 - u_1)] \}, c_1 = 10, \ f_1(x_1) = 2.5.
\]

The result means that the shortest working time of the problem is 2.5 hours, and the optimal allocation plan of the workforce is (groups): \( u_1^* = 2, \ u_2^* = 2, \ u_3^* = 1, \ u_4^* = 2, \ u_5^* = 1, \ u_6^* = 1, \ u_7^* = 1 \).

Similarly, for the other tasks in Table 3-1 (for example 4-7), we can also compute the optimized working time and corresponding workforce allocation.
3.4.2.2.2 The optimization result evaluation for the overall work in the hull block assembling procedure

The above calculation has optimized the working time of the operations in task 4-1 (double-layer-nested parallel task structure). Furthermore, we evaluate the optimization effect of the overall work’s hybrid relationship structure that is composed of series connection tasks and other types of tasks such as 4-1, 4-7.

First of all, we obtain the working time for assembling the new added amidships and the original rear ship block using historical data. It is shown in Table 3-4. Then, a three-point estimate technique is utilized. We use the most optimistic time, the most likely time and the most pessimistic time to find the range of production times that is in line with actual shipyard production. From this, we can get the average production time. As shown in Table 3-5, the estimated working time of each task is obtained according to actual shipyard production.

Table 3-4. The working hour obtained from experience

<table>
<thead>
<tr>
<th>Task</th>
<th>4-1</th>
<th>4-2</th>
<th>4-3</th>
<th>4-4</th>
<th>4-5</th>
<th>4-6</th>
<th>4-7</th>
</tr>
</thead>
<tbody>
<tr>
<td>working hours</td>
<td>4.5</td>
<td>1</td>
<td>2</td>
<td>0.5</td>
<td>1</td>
<td>0.5</td>
<td>5.5</td>
</tr>
</tbody>
</table>
Table 3-5. The estimated working hour of each task

<table>
<thead>
<tr>
<th>Node</th>
<th>Task</th>
<th>The estimated working time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>the most optimistic time</td>
</tr>
<tr>
<td>Shut of the new added amidships and the original rear ship block (4)</td>
<td>4-1</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>4-2</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>4-3</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>4-4</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>4-5</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>4-6</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>4-7</td>
<td>4.5</td>
</tr>
</tbody>
</table>

Through further statistics based on the above data, we can obtain Table 3-6:

Table 3-6. Statistical working hours

<table>
<thead>
<tr>
<th>Node</th>
<th>The estimated time</th>
<th>Estimate</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>the most optimistic time</td>
<td>the most likely time</td>
<td>the most pessimistic time</td>
</tr>
<tr>
<td>(2) Cutting off</td>
<td>27.9</td>
<td>34.5</td>
<td>41.9</td>
</tr>
<tr>
<td>(3) Segmented insert</td>
<td>2.4</td>
<td>3</td>
<td>4.5</td>
</tr>
<tr>
<td>(4) Join of the new added amidships and the original rear ship block</td>
<td>12.4</td>
<td>15</td>
<td>17.75</td>
</tr>
<tr>
<td>(5) Total closure of the first block and new rear ship block</td>
<td>15</td>
<td>17</td>
<td>23</td>
</tr>
<tr>
<td>Total working period</td>
<td>57.7</td>
<td>69.5</td>
<td>87.15</td>
</tr>
</tbody>
</table>

According to PERT three-point estimate technique, with a normal distribution based on central limit theorem, for the main processes, the mean value of the total working time: 70.48 hours; standard deviation: 2.85; and the final completion deadline: 72 hours. The probability of final completion at deadline: \( p = 70.19\% \).
Comparatively speaking, if we plan the operations using historical data, the relative probability cannot guarantee the working time requirement of the overall work. By optimizing the above operation working time, we compute the total work duration again and get the mean value of the total working time: 64.32; the standard deviation: 2.59; final completion deadline: 72 hours; and the probability of final completion at deadline: $p = 99.85\%$. These results indicate that the working time optimization, with the relevant workforce allocation to reduce the total operating time, can guarantee the ship block construction duration requirement.

3.5 Conclusion
Through a top-down refinement method to specialize product design and production decomposition in WBS, we propose three basic task structures that are widely adaptable in OKP companies, viz. tandem structure, parallel structure and double-level-nested parallel structure. Among these structures, the double-level-nested parallel task in OKP processes is the most difficult for working time optimization. Aiming at this problem, a discrete-nested-set DP to solve the workforce allocation and working time optimization problem is presented. The method is applied to the “Swire Ship” refitting and lengthening project in a shipbuilding company. The case study validates the feasibility and effectiveness of our method.

As future work, for diverse interim product flexible production lines in OKP, more research on the working time optimization problem with the constraints of product composition parameters such as production schemes, workers of various sorts and different types of manufacture equipment is needed.
Chapter 3 is based on the accepted manuscript (Mei et al., 2016, available online: http://www.tandfonline.com/10.1080/00207543.2015.1088972) published by Taylor & Francis in International Journal of Production Research.
CHAPTER 4 THE CLOSED-LOOP DYNAMIC PRODUCTION COST CONTROL AND
OPTIMIZATION OF INTERIM PRODUCTS BASED ON WORKING HOURS &
MANPOWER FOR OKP

4.1 Introduction

Generally speaking, the interim products in OKP are the prefabricated parts that are between the final product and raw materials when the OKP project is decomposed. The OKP work breakdown structure (WBS) is illustrated in the Fig. 3-1 of Chapter 3. An interim product in the OKP WBS indicates that a desired product state (e.g., a part) can be achieved from the starting product states (e.g., some components or raw materials). In OKP, the interim product is not only the operational unit of production but also a component of the work task decomposition for the final product; it is the component part of the stepwise formation of the final product. The interim products, for example, in shipbuilding include not only sub-segments, parts and components but also the outfitting pallet, module, unit and pipe fitting. Interim product specialization is the predominant production trend in modern OKP.

Based on Tu’s description, the design and production decomposition of the OKP product is modeled in a three-dimensional space, i.e., time dimension (T axis), product design dimension (Pd axis) and production specification dimension (Ps axis). Along the T axis, an OKP product is produced step by step, and the production data become increasingly clear. Along the Pd axis, an OKP product design (from a general specification to detailed components) is continually improved or perfected. Along the Ps axis, production is specified or decomposed from a general requirement or guideline into detailed processes. Moreover, work task relation structures in WBS, which are made up of unit structures: tandem structure, parallel structure and double-level-nested parallel structure, and assembly sequences usually are discrete and non-numerical
(Mei et al. 2016). A typical double-level-nested parallel task structure in OKP is shown in the Fig. 3-2 of Chapter 3. In Chapter 3, a dynamic programming (DP) based on discrete nested-set was proposed to solve workforce allocation and the corresponding working time optimization problem with discrete and non-numerical constraints in OKP.

As shown in Fig. 3-1, in OKP, an interim-product-oriented work decomposition method is normally applied, which has a top-down structure and simple-to-complex refinement. The purpose of the work decomposition is to enable design departments to divide various levels and types of interim products according to the production sector requirements, to allow departments of the OKP manufacturer to mark the production material that was selected in the product design procedure and to make workers complete a certain amount of jobs at the specified working position according to the prescribed production stage. Therefore, the work decomposition in OKP requires a close cooperation between production and product design.

OKP provides discrete production with complex structures. To some extent, planning and controlling the production of interim products in OKP are similar to planning and controlling projects. However, there are some differences between them. For planning and controlling OKP manufacturing, first, as discussed above, some of the work with discrete and non-numerical structures in WBS needs to be taken into account. Here, non-numerical structure is indicated as a more natural model of data. For example, the nested parallel structure can be regarded as the nested set of multiple discrete “graph” data structures, in which there is no operation sequence. A nested parallel task structure is three-dimensional: its space is defined by hierarchical structures and operation information. Second, OKP is characterized by product design uncertainty and changes in resource availability (Jiang et al. 2001, 2003). Third, lead time or makespan management is not the final objective of complicated OKP (e.g. shipbuilding). In OKP, working
time is not only related to scheduling but also associated with man-hour cost and production resource allocation (e.g., workforce allocation). The target of complicated OKP is to obtain the minimum cost (e.g., man-hour cost) based on the reasonable schedule of each work activity in production process.

The common production control and management method that OKP enterprises generally utilize is Network Planning Technology (e.g., Program Evaluation and Review Technique or PERT). However, the computer-aided planning software based on PERT, which is mostly oriented to the static problems of engineering projects’ early stage preparation work, such as planning, optimization, expense budget, etc., does not reflect the stochastic process and resource dependency in the process. Moreover, its results are based on probability and estimation. In OKP, work durations are changed dynamically due to product design uncertainty and changes in production resource availability. Production control systems of OKPs are concurrent, discrete-event dynamic systems for illustrating process activities. Therefore, PERT is not suitable for modeling a formal system specification for analysis. This research aims to offer an effective method for modeling complicated flexible manufacturing and to support the OKP dynamic cost control and optimization considering the complex production decomposition, product design uncertainties and changes in OKP.

Besides, in OKP engineering, man hour (or working time) is the main factor in cost measurement, and it is an important basis for reasonable enterprise planning and scheduling. The production target of OKP enterprises is that the OKP products are planned to be produced at the minimum cost based on the reasonable schedule of each work activity during the production period. However, as mentioned above, OKP manufacturing processes are complicated, and the event nodes are too numerous. Therefore, the mathematics implementation of the optimum plan
is very difficult, which means the working time and cost control in actual OKP are comparatively complicated. Therefore, we use the OKP interim products (e.g., the ship blocks in shipbuilding) as the focus of our research, presenting a practical OKP minimum cost model and its solution to achieve the minimum cost schedule.

Eventually, a framework for closed-loop dynamic production cost control and optimization in OKP is discussed in this chapter.

In brief, due to the particularity of flexible manufacturing in OKP, for example, shipbuilding, closed-loop production control is difficult. The “production control”, as a bottleneck, has restricted the overall development of OKP. The cost control in OKP is generally divided into active cost control and passive cost control. Passive cost control takes measures to achieve a reasonable cost before production considering various factors. Active cost control aims to control variable factors that occur in production process dynamically and promptly. Active cost control for flexible manufacturing in OKP is a dynamic procedure, constantly improving and perfecting the production results. In this work, we first propose a PERT-Petri method to dynamically optimize, and balance each task’s (process) construction period and cost in the OKP flexible interim production line. In OKP, flexible interim production line is mainly used, as productive resources (e.g. workforce, equipment) can be adjusted to actual production requirements. Then, a minimum cost model is obtained for the interim production; meanwhile, nonlinear theory is applied to solve and obtain the minimum construction cost (man-hour cost) within a specified period. Based on these studies, a closed-loop dynamic production cost control and optimization system in OKP is presented. We aim to analyze dynamic interim production cost control and optimization under different workforce allocation and working time scenarios in a closed-loop control system. This is novel for OKP manufacturing.
Based on optimal control theories and methods, the top to down schema of our work is as follows:

![Diagram](image)

Figure 4-1. The top to down schema of this work

Research of production control has been carried out for many decades, and the reports concerning production control in manufacturing in general are extensive. However, to best of our knowledge, there is only a relatively small number of meaningful references that discuss dynamic production control in OKP incorporating product design uncertainty and changes in resource availability. Even within these references, these studies either simply mention the topics or are indirectly related to our research. None of these papers has meaningfully addressed the dynamic production man-hour cost control considering the complex production decomposition, product design uncertainties and changes in OKP. Controlling and managing the production of interim products in OKP is very similar to controlling and managing projects. For the production
of OKP interim products, there are several difficulties to implement a closed-loop dynamic production cost control based on working hours and manpower: (1) How to effectively model an OKP system that is characterized by product design uncertainty and changes in resource availability (e.g. workforce); (2) In an OKP system, structural relationships (e.g. nested parallel task structure) and assembly sequences usually are discrete and non-numerical. How to coordinate variable workforce allocations to achieve reasonable working time in an OKP flexible manufacturing belongs to the constrained mixed discrete optimization problem, which is hard to describe as a unified mathematical optimization model (Mei et al. 2016). (3) How to comprehensively consider relevance between working time and cost to make a reasonable production schedule.

We provide an OKP minimum cost model based on the multilevel hierarchical PERT-Petri net, and the related closed-loop dynamic production cost control and optimization system.

4.2 Research background

As a preliminary study, Jiang et al. (2003) discussed automatic modeling of OKP systems by temporized object-oriented Petri Nets with changeable structure: Temporized object-oriented Petri nets with changeable structure (TOPNs-CS), which is an extension of OPNs-CS, is capable of modeling OKP systems subject to changes. This research work proposes an automatic approach to overcoming the difficulty in building complex TOPNs-CS models for an OKP system. TOPNs of production resources are simplified by the characteristic modeling elements. Message passing relations are classified into four protocols, each of which is characterized by its characteristic modeling elements. A formal description is given for product production structure (PPS) and production service structure (PSS) in an OKP environment to supply systematic and
easily usable data necessary for building the model. Algorithms are specified to transfer the data in terms of a formal description in an OKP environment into the characteristic modeling elements, and to identify the protocols of the message passing relations. With this approach, a TOPNs-CS model can be updated automatically to reflect changes in PPS and PSS as a result of the changes in a product and its processing processes.

As discussed by Jiang et al. (2003), an OKP system is characterized by uncertainties and changes. To produce a large variety of products in small batches, more diverse production resources have to be included in the system, and more flexibility has to be built into it. As a result, an OKP system is usually very complex. To model the complex OKP scenarios with uncertainties and changes effectively, TOPNs-CS that can be used for performance modeling of OKP systems is proposed. The research work presents an approach for automatic on-line reconstructing or modifying of TOPNs-CS models to accommodate the required complexity and eliminate human errors. TOPNs-CS is capable of performing modeling of OKP systems subject to changes. However, building a TOPNs-CS model of a production system can be complicated owing to the complexity of TOPNs-CS. This research work proposes an approach to simplify the TOPNs-CS model for OKP systems, which is necessary for constructing TOPNs-CS model of OKP systems automatically (Jiang et al. 2003):

1. To avoid the complexity of building a TOPNs of a production resource by directly determining all the modelling elements of TOPNs-CS, the TOPNs of the production resources have been described by the characteristic modelling elements and the timed initial marking. These characteristic are basic modelling elements from which dynamic attributes, including colour sets and timed expressions can be constructed
easily. Methods for deducing dynamic attributes to obtain TOPNs for four production resource classes are given.

2. To simplify the construction of message passing relations, which is one part of a TOPNs-CS model, the message passing relations are classified into four kinds of protocol, each of which is defined by the characteristic expression functions and the time delay sets. That is, if the kind of protocol to which the message passing relations of two or three production resources and their characteristic modelling elements are known, the message passing relations among these production resources can be determined.

3. In OKP environments, product production structure (PPS) and production service structure (PSS) represent the product structure and manufacturing processes as well as supplementary service operations. For easier mapping of PPS and PSS onto the characterised modelling elements and the characterised message passing relations, that determine the TOPNs-CS mode of an OKP system, PPS and PSS are formally defined. By using the formalised PPS and PSS, the product states, processes, production resources for processes, and routeings can be described semantically such that relevant data can be gathered simply and automatically.

4. Given static object-oriented Petri nets (OPNs), TOPNs of production resources can be formed easily by the characterised modelling elements of TOPNs. Consequently, the algorithms are defined to establish the mapping relationships between relevant process data contained in a formalised PPS along with PSS and the characterised modelling elements of TOPNs.
5. Message passing relations are divided into four different classes, each of which can be compactly described by its characterised message passing relation. An algorithm is suggested for transferring data related to routeing specified in formalised PPS and PSS into the characterised message passing relations. Once each individual characterised message relation is obtained, they can be integrated into a TOPNs-CS model.

6. A case study is supplied to illustrate how TOPNs-CS model building can be simplified by the characteristic modelling elements of TOPNs and the characteristic message passing relations, and how the process data in term of formalised PPS and PPS are mapped onto the characteristic modelling elements of TOPNs and the characteristic message passing relations by algorithms proposed in this chapter. It is also shown that the final TOPNs-CS model can be deduced by the available characteristic modelling elements of TOPNs and characteristic message passing relations.

4.3 The dynamic production cost control and optimization based on the multilevel hierarchical PERT-Petri net model

In an OKP system, duration of working process (or task) is stochastic and is influenced by product design uncertainty and resource changes in complex WBS. In process simulation, there are some models that can be used, e.g. PERT and Petri net. As described by Zhang et al. (2004), although the PERT model has been successfully applied to critical path analysis, job completion capability analysis, progress control and time & cost calculation, there are still some disadvantages in complex process modeling and simulation (Ghomi et al. 2002; Liberatore 2008;
Seong et al. 2014; Acebes et al. 2014; Tesfaye et al. 2015): First, it cannot reflect the stochastic process and resource dependency in the process. Second, its calculation accuracy depends mainly on the accuracy of parameters, such as the earliest time of node $i$, $TE_i$, the latest time of node $i$, $TL_i$, etc. In general, the parameters are obtained through probability and estimation. Therefore, a PERT model cannot meet the requirements of process simulation. In order to make up for the above deficiencies, and carry out the real-time and dynamic production cost control in complicated OKP, Petri net models that constitute the OKP model library should be considered to support PERT models.

In the previous studies, colored Petri nets with changeable structures (CPN-CS) and temporized object-oriented Petri Nets with changeable structure (TOPNs-CS) were effective for modeling an OKP system that is characterized by product design uncertainty and changes in resource availability over time (Jiang et al. 2001, 2003). Nevertheless, for some OKPs with a multilevel-hierarchical structure, e.g., ship building production, which often require a simple-to-complex approach through the top-down refinement of a complex production task structure (as shown in Fig. 3-1), Petri nets also cannot be easily used to model complex dynamic hierarchical systems. It would be difficult to build, debug and change the model when the production system configuration changes.

Given the characteristics of complex production process simulation, a multilevel hierarchical PERT-Petri net model (MLHPP) that combines the advantages of PERT and Petri net models, and makes up for the shortcomings of the two models, is needed for OKP. This PERT-Petri net model will be used for complex production process simulation. Section 4.3.1 presents the multilevel hierarchical PERT-Petri net model; and Section 4.3.2 describes the
recursive algorithm of this model. Based on the model construction of complex production process simulation in OKP and its analysis, a minimum cost model, which is aimed at dynamically controlling and optimizing man-hour cost of interim products under variable workforce allocation and working time scenarios in a closed-loop control system, is obtained in Section 4.3.2.

4.3.1 Definition of the multilevel hierarchical PERT-Petri net model

Zhang et al. (2004) introduced the multilevel PERT-Petri net model based on an analysis of the application of PERT and Petri net on process simulation. For the hierarchical structure model, this model divides the process into multiple levels and then uses the PERT model to build the workflow simulation and analysis model on the top and intermediate levels. The Petri net model is used to simulate a basic event procedure in the workflow on the bottom level. When building the multilevel PERT-Petri model, a model library that consists of the Petri net model units of the basic production processes is also used. Based on our previous research presenting a method for workforce allocation and working time optimization with discrete and non-numerical constraints in OKP (Mei et al. 2016), various time parameters for the upper level PERT model can be obtained through bottom level event Petri net (e.g., CPN-CS and TOPNs-CS) simulation and analysis. Then, these real-time changeable parameters will be used in the upper level PERT models for dynamically optimizing and balancing each work activity (or task/process) production period and cost (in OKP, as discussed in Section 4.3.2, supposing that working time and the corresponding man-hour cost have a linear relation.) under the constraint of total construction period. Thus, we can adjust and optimize the resources, costs and time limits in OKP interim production, and the simulation, analysis and optimization of workflow will be
achieved. However, Zhang et al. (2004) simply propose the general modeling method and simulation algorithm for the complicated process flow, and do not present the related production control and optimization algorithms and the bottom level event Petri net model, which are the key determining factors for the whole OKP planning and control system. According to Zhang et al. (2004), we further define MLHPP for interim product production process simulation and analysis in OKP as the following formalized recursive definition:

$$MLHPP = (PM, SM, SP, P, N, F, MF, T, C)$$

In this PERT-Petri net model, the symbols’ meanings are as follows:

- **PM** is the Parent-MLHPP model identification. $PM = NULL$ indicates that this model is the top-level model.

- **SM** = $\{SM_i\}_{i=1}^{l}$ is the object set of sub-MLHPP ($l$ denotes the number of sub-MLHPPs, $i \in [1, l]$). $SM_i$ is also the MLHPP model, and if there is not a sub-MLHPP model in the process, $SM = Null$.

- **SP** = $\{SP_j\}_{j=1}^{J}$ is the object set of the sub-Petri net model ($J$ denotes the number of sub-Petri nets, $j \in [1, J]$), and if there is no sub-Petri net model in the process, $SP = Null$.

- **P** is the process set, and **N** is the node set; both **P** and **N** are finite sets.

- **F** denotes the connection relations among processes and nodes of the set $P \times N \cup N \times P$.

- **MF** denotes the binary relation among the models and processes of the set $SM \times P \cup SP \times P$. 

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\( T : \{ t, T_s, T_f, ES, EF, LS, LF, TF, FF \} \), \( T \in [0, \infty] \), \( T_i \) is the time parameter set (\( t \): the time duration, \( T_s \): the start time, \( T_f \): the finish time, \( ES \): Earliest Start Time, \( EF \): Earliest Finish Time, \( LS \): Latest Start Time, \( LF \): Latest Finish Time, \( TF \): Total Float Time, \( FF \): Free Float Time) in process \( i \).

\( C : \{ C_i(r) \}_{r=1}^{R} \), \( C \in [0, \infty] \), \( C \) is the resources consumption set, and \( C_i(r) \) is the resources consumption of resource \( r \) in process \( i \).

Here, the bottom level Petri net models of the OKP model library are regarded as the basic model units that are included in \( SP \). In the previous research, CPN-CS and TOPNs-CS (Jiang et al. 2001, 2003) are used to model the comparatively simple production structures on the bottom level of OKPs.

In an OKP system, the graphic description of interim product production process simulation and analysis is illustrated as follows. \( T \) axis denotes time dimension and \( P \), axis denotes production specification dimension.
4.3.2 **Recursive simulation algorithm of the multilevel hierarchical PERT-Petri net model**

In this section, the recursive simulation algorithm of the multilevel hierarchical PERT-Petri net model is discussed.

**The algorithm of recursive simulation:**

Zhang et al. (2004) describe the algorithm as follows: the overall simulation algorithm includes two parts - the simulation calculation of the Petri net model and the calculation of the PERT model. The Petri net model calculation aims at the processes with high uncertainty. For the micro stochastic processes of concrete events, the parameter metrics such as process time and recourse cost are obtained through Petri net simulation calculation. The PERT model is used to achieve performance metrics, such as time parameter and resource cost, that are required for process evaluation and decision making. The simulation calculation uses the bottom-up method, which aims to obtain the key procedure time parameters from Petri net models on the bottom...
level, to feedback the key time parameters to PERT models on the upper level, and then to obtain the overall procedure’s performance index by PERT simulation model calculation. The algorithm model has a hierarchical structure, and the algorithm should not be constrained by run times. Because the mid-level model simulation calculation can adopt the same algorithm model, the recursive model will be used to perform the overall model calculation.

Based on the general recursive algorithm described by Zhang et al. (2004), a detailed recursive simulation algorithm of MLHPP incorporating feedback control is as follows.

Set \( M_0 \) as the top-level PERT model, and \( PM = \text{Null} \). The recursive algorithm is \( \text{fun}_\text{mlhpp}(\text{mlhpp } M) \). The return values are \( T \) and \( C \). The recursive simulation algorithm of MLHPP is defined in the following steps:

**Step 1:** Obtain the number \( I \) of \( SM \). If \( I = 0 \), then begin Step 4; otherwise, \( i \leftarrow 1 \);

**Step 2:** Recursively call \( \text{fun}_\text{mlhpp}(\text{SM}_i) \) and return the time parameter \( T_i \) and resource consumption \( C_i \) (e.g., workforce);

**Step 3:** \( i = i + 1 \); if \( i > I \), then begin Step 4; otherwise, begin Step 2;

**Step 4:** Obtain the number \( J \) of Petri net model set \( SP \) for this level model. If \( J = 0 \), then begin Step 6; otherwise, \( j \leftarrow 1 \).

**Step 5:** Set or obtain the existing resource information.

**Step 5-1:** First, schedule tasks (production processes) in OKP by our proposed method (Mei et al. 2016).

There are three basic task structures: the tandem structure; the parallel structure; double-level-nested parallel task structure. For the tandem task structure, network planning methods have been able to optimize the production planning according to the predecessor-successor
relationship of operations. For the parallel structure, it can be solved by the traditional dynamic programming. For double-level-nested parallel task structure, a method for working time optimization and workforce allocation with discrete and non-numerical constraints in complicated OKP is proposed (Mei et al. 2016). The working time optimization and workforce allocation with discrete and non-numerical constraints is illustrated in the Fig. 3-3 of Chapter 3.

In Fig. 3-3, MRCGA denotes the matrix real-coded genetic algorithm. Each operation of the main-level \( i \) needs at least one group of workers to complete work. Also, the nested-level task \( i^* \) needs at least one group of workers. Here, for the parallel relationship of the operations, there is no operation sequence (i.e. dynamic optimization process for solution), which implies making the sequence of decisions in accordance with certain conditions the optimal. Scheduling operations in the main-level \( i \) and operations in the nested-level \( i^* \) is similar to scheduling processes and threads in computer operating system. A discrete nested-set DP model for solving the optimization problem of double-level-nested parallel task structure is indicated as follows:

Step variables: There are \( m + 1 \) phases in the whole process.

Decision variables: \( u_p \) is the number of the workforce units allocated to the \( p-th \) phase, \( p = 1, 2, \cdots, m + 1 \). Let the nested-level task \( i^* \) be the \( (m + 1)-th \) phase.

State variables: \( c_p \) indicates the number of cumulative workforce units allocated to the phases from \( p \) to \( m+1 \). Obviously, \( c_1 = W \) (\( W \) is the number of total workforce units), \( m-p+2 \leq c_p \leq W-p+1, p = 2,3,\ldots, m+1 \).

State transition equation: \( c_{p+1} = c_p - u_p \).

Set of admissible decisions: \( D_p(c_p) = \{ u_p \parallel u_p \leq \min(c_p, W - m) \} \), \( u_p \) is positive integer.
Step objective function: \( v_p(u_p) = \max \left\{ T_p(u_p) \right\} \) shows the max time needed for completing the \( p \)-th operation with the allocated \( u_p \) workforce units.

Optimal objective function: \( f_p(c_p) \) denotes the minimum time needed by \( c_p \) workforce units to complete the operations \( p, \ldots, m + 1 \) in all workforce allocation schemes.

The discrete nested-set DP equation is presented as follows:

\[
\begin{align*}
    f_p(x_p) &= \min_{u_p \in D_p(c_p)} \{ \max[T_p(u_p), f_{p+1}(c_p-u_p)] \}; \quad p = m, \ldots, 1; \quad 1 \leq u_p \leq W-m \\
    f_{m+1}(c_{m+1}) &= T_{m+1}(u_{m+1}); \quad u_{m+1} = c_{m+1}; \quad T_{m+1}(u_{m+1}) \leftarrow fun\_MRCGA(u_{m+1}); \quad 1 \leq u_{m+1} \leq W-m
\end{align*}
\]

(3-1)

Step 5-2: Then the CPN-CS and TOPNs-CS models (Jiang et al. 2001, 2003) will be used to simulate the production and identify the bottleneck task(s). Human schedulers may re-allocate the work units in tasks (processes) accordingly to smooth the production flow. We can obtain the time parameter \( T_j \) and resource consumption \( C_j \) in these Petri net models.

Step 6: \( j = j + 1 \). If \( j > J \), then begin Step 7; otherwise, begin Step 5. The algorithm process of Step 5 and Step 6 is as follows:

For all \( SP_j \), \( j \in [1, J] \)

\[
[T_j, C_j] \leftarrow fun\_THOCPN-CS(SP_j)
\]

Step 7: According to \( MF \), obtain all of the \( P \) that do not have the sub-models. Obtain the corresponding \( T^* \) and \( C^* \) according to the rated value or empirical value.

Step 8: Using \( T_j, C_j, T^*, C^* \), apply parameter calculation algorithms of PERT model (e.g. Castro et al. 2008; Castro et al. 2014; Seong et al 2014) to get required parameters (e.g. working time thresholds) of work activities in OKP interim production under the constraint
of total construction period. Here, total construction period is overall construction time period from start to finish, as well as a projected completion date of the production process in PERT net. The minimum cost model based on PERT can be obtained, which will be introduced as follows. Achieve the actual working time of each work activity and the minimum man-hour cost $K$ of this multilevel hierarchical PERT-Petri net model for OKP.

Step 9: Feedback recursive control algorithm for error compensation. Traditional PERT open-loop control algorithms can be used in this step.

The algorithm terminates.

The whole recursive algorithm process is shown in Fig. 4-3.

Figure 4-3. Recursive simulation algorithm process
**The quadratic programming model for the minimum cost of OKP interim production:**

In OKP, product design uncertainty and changes in resource availability lead to different production plans and workforce allocation schemes, which further brings about the working time variance of each work task in a production process. Furthermore, the working time of each work task directly affects overall production cost. Although planning and controlling the production of interim products in OKP is similar to planning and controlling projects, lead time or makespan management is not the final objective of complicated OKP. The total minimum production cost that depends on the working time of each work activity is the production target of OKP enterprises.

MLHPP dynamically optimizes and balances each work activity’s production period and cost under the constraint of total construction period; then the minimum cost model for the interim production in PERT level can be obtained.

In this section, we focus on the analysis of the man-hour cost control and optimization of OKP interim production in different workforce allocation schemes. Based on the OKP interim production upper-level PERT diagram, the minimum cost model optimizes the working activity duration and achieves cost control based on the flexible and compressible time of working activities. As indicated above (Step 8), and from the above analysis in this section, we can obtain the minimum cost model according to relevant parameters. The specific problem description is as follows.

Based on the problem description from Lin et al. (2007), there are \( m \) work activities and \( n \) event nodes. All of the work activities in the OKP project are \( P_{i,j} \) (from event \( i \) to \( j \)) and its set \( S = S^{(1)} \cup S^{(2)} \). In the \( S \) set, \( S^{(1)} \) is the set of all of the work activities that can be accelerated,
and \( S^{(2)} \) is the set of the work activities that cannot be accelerated. According to \( T_i, C_i, T_j, C_j, T^*, C^* \) in Section 4.3.2 (Step 8), apply parameter calculation algorithms of PERT model to get the required parameters (\( t_{\text{max}}^{i,j} \) and \( t_{\text{min}}^{i,j} \)) of work activities. Suppose the work activity \( p_{i,j} \) (from event \( i \) to \( j \)), \( p_{i,j} \mid p_{i,j} \in s = \{1, 2, \ldots, m\} \), and its longest duration time is \( t_{\text{max}}^{i,j} \). In the case of accelerating, the ultimate compressed time is \( t_{\text{min}}^{i,j} \), and the corresponding unit man-hour costs are \( K_{\text{min}}^{i,j} \) and \( K_{\text{max}}^{i,j} \). (During the accelerating procedure of each OKP work activity, suppose its working time and the corresponding cost have a linear relation.).

When \( t_{\text{max}}^{i,j} > t_{\text{min}}^{i,j} \), then \( K_{\text{max}}^{i,j} > K_{\text{min}}^{i,j} \), and the work activity \( p_{i,j} \) maximum compression time value is \( t_{\text{max}}^{i,j} - t_{\text{min}}^{i,j}, p_{i,j} \in S^1 \).

When \( t_{\text{max}}^{i,j} = t_{\text{min}}^{i,j} \), the work activities \( p_{i,j} \) cannot be accelerated, and \( K_{\text{max}}^{i,j} = K_{\text{min}}^{i,j} \) and \( p_{i,j} \in S^2 \).

\( v_{i,j} \) is the time compression value in the OKP interim production planning. \( 0 \leq v_{i,j} \leq (t_{\text{max}}^{i,j} - t_{\text{min}}^{i,j}), v_{i,j} \in R \). And \( v_{i-j} = t_{\text{max}}^{i-j} - v_{i-j} \).

During the accelerating procedure of each OKP work activity, suppose its working time and the corresponding cost have a linear relation.

In summary, the minimum cost model based on the multilevel hierarchical PERT-Petri net for dynamic control and optimization in OKP is indicated as follows:

\[
\min K = \sum_{p_{i,j} \in S^1} \left[ \frac{(K_{\text{max}}^{i,j} - K_{\text{min}}^{i,j}) \cdot (t_{\text{max}}^{i,j} - v_{i,j})}{t_{\text{max}}^{i,j} - t_{\text{min}}^{i,j}} + K_{\text{max}}^{i,j} \right] \cdot v_{i,j} + \sum_{p_{i,j} \in S^2} K_{\text{min}}^{i,j} \cdot t_{\text{max}}^{i,j}
\]

\( = \sum_{p_{i,j} \in S^1} \left[ -G \cdot (v_{i,j})^2 + (G \cdot t_{\text{max}}^{i,j} + K_{\text{min}}^{i,j}) \cdot v_{i,j} \right] + \sum_{p_{i,j} \in S^2} K_{\text{min}}^{i,j} \cdot t_{\text{max}}^{i,j} \) (4-1)
s.t. \( t_{\text{min}}^{i,j} \leq v_{i,j} \leq t_{\text{max}}^{i,j} \), \( v_{i,j} \in R \).

Here, \( v_{i,j} = t_{\text{max}}^{i,j} - v_{i,j} \), and \( v_{i,j} \) is the decision variable. \( K \) denotes the total man-hour cost. \( G \) denotes \( \frac{K_{\text{max}}^{i,j} - K_{\text{min}}^{i,j}}{t_{\text{max}}^{i,j} - t_{\text{min}}^{i,j}} \).

In OKP, interim product manufacturing processes are complicated, and the event nodes are numerous. Multiple work activities are involved in the minimum cost optimization. Therefore, the algorithm implementation for the optimum model is very difficult.

The minimum cost model is a quadratic programming model. We performed the following analysis: the nonlinear programming objective function (4-1) is comprised of the polynomial of each work activity; each polynomial is the quadratic formula of \( v_{i,j} \); the objective function is to obtain the minimum cost of the total production and the threshold constraints are linear; there are no constraint relationships among various work activities’ polynomials; and individual values of polynomials have the characteristic of diminishing marginal returns.

We used Excel for optimization and to analyze the limit reports to correct errors (Section 4.4.2). When using Excel to solve the nonlinear programming problem, the obtained results are mostly local optimal results. However, Excel provides an accurate limit report function, which helps to further amend the results in the solving process. The case studies show that the final results approximate the global optimization better than the local optimal results in the convergence range. The solution is simple and practical and provides support for cost optimization in OKP interim production.
4.4 Case study for the minimum cost control and optimization

In this section, the case study for the minimum cost control is provided.

4.4.1 Case description

We use the cost control and optimization of the ship body section building as the case study. In the Product Production Structure (PPS), the production level of the ship body section building is the mid-level of the overall ship building. This mid-level production simulation is made by the upper level PERT model, which indicates the structure constraint relationship of the ship body section manufacture. To illustrate the real-time parameter indicators, which are obtained from bottom-level Petri net simulation calculation, the graphic expression of the resembling Petri node is applied to describe each node in the PERT diagram.

In a shipyard, the manufacture of a ship block involves the following working processes (Lin et al. 2007): (1) supply preparation, (2) steel material processing, (3) graphic design, (4) the ship body section outfitting manufacture, (5) frame manufacture, (6) body section structure manufacture, (7) pallet collection & distribution, (8) ship body section pre-outfitting, (9) ship body section coating, and (10) the ship body section closure construction process. In terms of these activities, the MLHPP planning diagram for building the ship body section is illustrated in Fig. 4-4:
Figure 4-4. The MLHPP planning diagram of ship body section construction

\[ T_{i5} \] means the logical judgment at the beginning of the work activity \( i \), whether there is enough workforce and whether the immediate predecessor activity is completed. \( T_{iE} \) means the duration of the work activity \( i \). \( P_i \) means the initial state of the work activity \( i \). \( P_i^s \) indicates the persistent state of the work activity \( i \). \( P_i^e \) indicates the end of the work activity \( i \).

We need to determine the actual operation time of each work activity. The shipbody building work should be performed with minimum cost.

To verify the minimum cost model, the parameter value range of each work activity decision variable is obtained from practical production (Lin et al. 2007) and listed in Table 4-1. Based on the minimum man-hour cost model (4-1), Table 4-1 and Fig. 4-4, we can obtain the specific quadratic programming model as follows:
\[ MinC = (0.825 - 0.025 \cdot r_{1,2}) \cdot r_{1,2} + (0.85 - 0.016 \cdot r_{1,3}) \cdot r_{1,3} + (1.3 - 0.05 \cdot r_{1,4}) \cdot r_{1,4} + \\
(1.05 - 0.025 \cdot r_{2,5}) \cdot r_{2,5} + (1.05 - 0.05 \cdot r_{2,3}) \cdot r_{2,3} + (1.15 - 0.025 \cdot r_{3,6}) \cdot r_{3,6} + \\
(0.7 - 0.0375 \cdot r_{4,7}) \cdot r_{4,7} + (1 - 0.033 \cdot r_{5,8}) \cdot r_{5,8} + (0.8625 - 0.0125 \cdot r_{6,8}) \cdot r_{6,8} + \\
(1.05 - 0.05 \cdot r_{6,7}) \cdot r_{6,7} + (1.3 - 0.1 \cdot r_{7,9}) \cdot r_{7,9} + (2 - 0.2 \cdot r_{8,9}) \cdot r_{8,9} + \\
(1.1 - 0.1 \cdot r_{8,10}) \cdot r_{8,10} + 0.9 \times 6 \]

\[ s.t. \quad r_{1,2} \in [17, 21] \quad r_{1,3} \in [9, 15] \quad r_{1,4} \in [7, 11] \quad r_{2,5} \in [18, 22] \quad r_{2,3} \in [9, 13] \quad r_{3,6} \in [20, 24] \quad r_{4,7} \in [4, 8] \quad r_{5,8} \in [6, 12] \quad r_{6,8} \in [5, 13] \quad r_{6,7} \in [3, 5] \quad r_{7,9} \in [4, 6] \quad r_{8,9} \in [5, 6] \quad r_{8,10} \in [6, 6], \quad r_{9,10} \in [6, 6]. \]

Table 4-1. The parameters of the ship body section construction

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<th>( v_{i,j} )</th>
<th>( r_{i,j}^{\min} \leq v_{i,j} \leq r_{i,j}^{\max} )</th>
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<th>( K_{i,j}^{\max} )</th>
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<tr>
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Table 4-1. The parameters of the ship body section construction (continued)

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<tr>
<td>i</td>
<td>P_{i,j}</td>
<td>t_{i,j} ∈ [a_1, a_2]</td>
<td>v_{i,j}</td>
<td>0 ≤ v_{i,j} ≤ (t_{i,max} - t_{i,min})</td>
<td>v_1 = v_{i,j}</td>
<td>t_{i,j} = a_2</td>
<td>K^{i,j}_{min}</td>
<td>K^{i,j}_{max}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>12</td>
<td>P_8,9</td>
<td>t_{8,9} ∈ [5, 6]</td>
<td>v_8,9 ∈ [0, 1]</td>
<td>v_8,9 ∈ [5, 6]</td>
<td>0.8</td>
<td>1.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>P_8,10</td>
<td>t_{8,10} ∈ [4, 6]</td>
<td>v_8,10 ∈ [0, 2]</td>
<td>v_8,10 ∈ [4, 6]</td>
<td>0.5</td>
<td>0.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>P_9,10</td>
<td>t_{9,10} ∈ [6, 6]</td>
<td>v_9,10 ∈ [0, 0]</td>
<td>v_9,10 ∈ [6, 6]</td>
<td>0.9</td>
<td>0.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Here, i indicates the work activity, and P_{i,j} means the code name of the work activity. 

\[ t_{i,j} \] shows the required working time per day.

4.4.2 Solutions

The methods and theory for quadratic programming are well established. A variety of methods are commonly used, including the interior point method, active set method, augmented Lagrangian method, etc.

In this case, \( v_{i,j} \) is the decision argument of the corresponding working process. The corresponding rush hour cost, i.e. cost during the accelerating period of each OKP work activity, is shown as follows.

\[
\frac{(K_{i,j} - K_{i,j})^* (t_{i,max} - v_{i,j})}{t_{i,max} - t_{i,min}} + K_{i,j}^{max} \quad (4-2)
\]

The constraint matrix is as follows (there is no constraint relationship among the various decision parameters):
There are various types of mathematical software packages that can be utilized for the quadratic programming solution, such as LINDO (LINDO Systems Inc., Chicago, Illinois, USA), MATLAB (MathWorks, Natick, Massachusetts, U.S.A), SAGE, etc. We used Excel to solve the quadratic programming model in this case. The parameter selection in this case is as follows: longest operation time 300 s; number of iterations 200; precision 0.00001; permissible error 5%; and degree of convergence 0.0001. The optimization results are shown in Tables 4-2 and 4-3.

Table 4-2. The limit report

<table>
<thead>
<tr>
<th>Cell</th>
<th>Variable name</th>
<th>Lower limit</th>
<th>Result</th>
<th>Objective cell</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$34</td>
<td>variable 1</td>
<td>17</td>
<td>79.6593</td>
<td>21</td>
<td>79.1593</td>
</tr>
<tr>
<td>$B$34</td>
<td>variable 2</td>
<td>9</td>
<td>79.1593</td>
<td>15</td>
<td>81.8545</td>
</tr>
<tr>
<td>$C$34</td>
<td>variable 3</td>
<td>7</td>
<td>79.1593</td>
<td>11</td>
<td>80.7593</td>
</tr>
<tr>
<td>$D$34</td>
<td>variable 4</td>
<td>18</td>
<td><strong>78.959</strong></td>
<td>22</td>
<td>79.159</td>
</tr>
<tr>
<td>$E$34</td>
<td>variable 5</td>
<td>9</td>
<td><strong>79.159</strong></td>
<td>13</td>
<td>78.959</td>
</tr>
<tr>
<td>$F$34</td>
<td>variable 6</td>
<td>20</td>
<td><strong>78.959</strong></td>
<td>24</td>
<td>79.159</td>
</tr>
<tr>
<td>$G$34</td>
<td>variable 7</td>
<td>4</td>
<td>79.1593</td>
<td>8</td>
<td>80.1593</td>
</tr>
<tr>
<td>$H$34</td>
<td>variable 8</td>
<td>6</td>
<td>79.1593</td>
<td>12</td>
<td>81.5953</td>
</tr>
<tr>
<td>$I$34</td>
<td>variable 9</td>
<td>5</td>
<td>79.1593</td>
<td>13</td>
<td>84.2593</td>
</tr>
<tr>
<td>$J$34</td>
<td>variable 10</td>
<td>3</td>
<td>79.1593</td>
<td>5</td>
<td>80.4593</td>
</tr>
<tr>
<td>$K$34</td>
<td>variable 11</td>
<td>4</td>
<td>79.1593</td>
<td>6</td>
<td>79.7593</td>
</tr>
<tr>
<td>$L$34</td>
<td>variable 12</td>
<td>5</td>
<td>79.3593</td>
<td>6</td>
<td>79.1593</td>
</tr>
<tr>
<td>$M$34</td>
<td>variable 13</td>
<td>4</td>
<td>79.1593</td>
<td>6</td>
<td>79.3593</td>
</tr>
</tbody>
</table>
Table 4-3. The minimum cost and the final results

| Objective cell (minimum value) | | |
|-------------------------------|-------------------------------|
| $A$37                         | the minimum cost              | 79.1593                     |

| Variable Cell | | |
|----------------|-------------------------------|
| $A$34          | variable 1                    | 21                          |
| $B$34          | variable 2                    | 9                           |
| $C$34          | variable 3                    | 7                           |
| $D$34          | variable 4                    | 22                          |
| $E$34          | variable 5                    | 9                           |
| $F$34          | variable 6                    | 24                          |
| $G$34          | variable 7                    | 4                           |
| $H$34          | variable 8                    | 6                           |
| $I$34          | variable 9                    | 5                           |
| $J$34          | variable 10                   | 3                           |
| $K$34          | variable 11                   | 4                           |
| $L$34          | variable 12                   | 6                           |
| $M$34          | variable 13                   | 4                           |

4.4.3 The quadratic programming result correction and analysis

For the nonlinear programming problem, there is no method to find optimal solutions. The majority of nonlinear programming problem solutions that the mathematical software can offer are only local optimal solutions. However, the software tools offer the exact limit reporting function. Based on the limit reports, we can further modify the optimization results according to the specific problem-solving process and allow local optimal solutions to further approximate optimal solutions.

In this case, the initial result is $Min K = 79.15$. We analyzed the limit report (Table 4-2). The limit report in Excel provides a different type of “sensitivity analysis” information and is created by re-running the optimization model with each decision variable (changing cell) in turn as the objective (both maximizing and minimizing), and all other variables held fixed. The “lower limit” for each variable shows the smallest value that a variable can take while satisfying the constraints and holding all of the other variables constant. The “upper limit” is the largest
value the variable can take under these circumstances. Compared to variable limits (underlined or bold in Table 4-2), the final variable values (Table 4-2) of the task activities (2-5, 2-3, 3-6) have some deviations. Therefore, the results need to be further improved. Because there is no constraint relation among various polynomials in this case, we check the minimum cost calculation ($MinC$) of the working activities 2-5, 2-3, and 3-6 and obtain the corrected results as shown in Table 4-4. According to Table 4-4, we modify the corresponding variable values $v_{i,j}$ of the work activities ($v_{2,5} = 18; v_{2,3} = 13; v_{3,6} = 20$). The final values of the minimum cost and the actual accelerating working time $v_{i,j}$ are shown in Table 4-5.

Table 4-4. The corrected results of three work activities' errors

<table>
<thead>
<tr>
<th>Work activity</th>
<th>Cost value with error</th>
<th>The minimum cost value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-5</td>
<td>11 ($v_{2,5} = 22$)</td>
<td>10.8 ($v_{2,5} = 18$)</td>
</tr>
<tr>
<td>2-3</td>
<td>5.4 ($v_{2,3} = 9$)</td>
<td>5.2 ($v_{2,3} = 13$)</td>
</tr>
<tr>
<td>3-6</td>
<td>13.2 ($v_{3,6} = 24$)</td>
<td>13 ($v_{3,6} = 20$)</td>
</tr>
</tbody>
</table>
Table 4-5. Comparison of the two methods for calculating the optimal results
(Quadratic programming; genetic algorithm)

<table>
<thead>
<tr>
<th>Actual accelerating working time $v_{i,j}$ (day)</th>
<th>Quadratic programming model, (Excel tools)</th>
<th>Genetic Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v_{1,2}=0$ $v_{i,3}=6$ $v_{4, i}=0$ $v_{5,2,5}=4$ $v_{2,3}=0$</td>
<td>$v_{1,2}=0$ $v_{i,3}=6$ $v_{4, i}=0$ $v_{5,2,5}=4$ $v_{2,3}=4$</td>
<td></td>
</tr>
<tr>
<td>$v_{3,6}=0$ $v_{4,7}=4$ $v_{5,8}=6$ $v_{6,8}=8$</td>
<td>$v_{3,6}=4$ $v_{4,7}=4$ $v_{5,8}=6$ $v_{6,8}=8$</td>
<td></td>
</tr>
<tr>
<td>$v_{6,7}=2$ $v_{7,9}=2$ $v_{8,9}=0$ $v_{8,10}=2$</td>
<td>$v_{6,7}=2$ $v_{7,9}=2$ $v_{8,9}=1$ $v_{8,10}=2$</td>
<td></td>
</tr>
<tr>
<td>The actual working time of each work activity $v'_{i,j}$ (day)</td>
<td>$v'<em>{1,2}=21$ $v'</em>{i,3}=9$ $v'<em>{4, i}=7$ $v'</em>{2,5}=18$ $v'_{2,3}=13$</td>
<td>$v'<em>{1,2}=21$ $v'</em>{i,3}=9$ $v'<em>{4, i}=11$ $v'</em>{2,5}=18$ $v'_{2,3}=9$</td>
</tr>
<tr>
<td>$v'<em>{3,6}=20$ $v'</em>{4,7}=4$ $v'<em>{5,8}=6$ $v'</em>{6,8}=5$ $v'<em>{6,7}=3$ $v'</em>{7,9}=4$ $v'<em>{8,9}=6$ $v'</em>{8,10}=4$</td>
<td>$v'<em>{3,6}=20$ $v'</em>{4,7}=4$ $v'<em>{5,8}=6$ $v'</em>{6,8}=5$ $v_{6,7}=3$ $v_{7,9}=4$ $v_{8,9}=5$ $v_{8,10}=4$</td>
<td></td>
</tr>
<tr>
<td>The minimum cost $Min K$ [ten thousand (monetary unit)]</td>
<td>78.55</td>
<td>80.35</td>
</tr>
</tbody>
</table>

As illustrated in Table 4-5, the calculation results show that the quadratic programming model can search the optimization result in the given range of decision variables. We utilize the Newton search method (forward difference method). The minimum cost $Min K = 78.55$. In GA’s (genetic algorithm) solution, the population size is 50, the crossover probability is 0.6, mutation probability is 0.06 and the evolutionary times are 80. The optimized results in Table 4-5 are obtained by using MATLAB 7.11.0.
The heuristic algorithms can find solutions among all possible ones, and sometimes these algorithms can be accurate; however, they do not guarantee that the best will be found. Through comparisons, as an optimization method GA shows certain instability with the data in our case studies.

The minimum cost model, which is based on the multilevel hierarchical PERT-Petri net in OKP, conforms to the characteristics of quadratic programming. Considering the following features in our minimum cost model, (1) individual values of polynomials in the objective function have the characteristic of diminishing marginal returns; (2) the threshold constraints are linear; and (3) there is no constraint relationship among various work activity polynomials - we use Excel for optimization and to analyze the limit reports to correct errors. The case final result approaches the global optimal solution instead of the local ones. The method is simple and easy to be applied.

4.5 A closed-loop production cost dynamic control and optimization system

Due to uncertainties in OKP, such as product design changes, manufacturing process changes, supply changes and unexpected events, production needs to be controlled dynamically. Therefore, we propose a closed-loop dynamic production cost control and optimization system. The system, as illustrated in Fig. 4-5, consists of MLHPP and the minimum cost model for the production of interim products in OKP. Because of complex production decomposition, product design uncertainties and changes in OKP, production cost dynamic control and optimization is required for timely solutions. The multilevel hierarchical PERT-Petri net structure, the unique feature of the MLHPP simulation model, makes it easy and flexible to simulate complicated
production processes and frequent changes in the OKP interim product flexible production line for production cost dynamic control.

The switches in Fig. 4-5 imply that the dynamic production control system has two working states, simulation state and real-time control state, which can be switched between each other. When the system works on simulation state, it plans and controls the production man-hour cost under different scenarios. When it works on the real-time control state, it dynamically controls the production cost in real time.

Figure 4-5. A closed-loop production cost dynamic control and optimization system

Through the closed-loop dynamic production cost control and optimization system, the flexible OKP interim production based on working hours & manpower can be dynamically planned, and the building cost can be controlled to cope with disturbances.
4.6 Conclusion

In this work, the dynamic production cost control and optimization in OKP is achieved under different workforce allocation and working time scenarios, and a closed-loop cost-control system is presented.

Although some useful research results for OKP control have been achieved, there are still some limitations that require further research. First, the closed-loop production control system needs to be further studied and developed considering system stability and robustness. Second, for judging and optimizing interim product production processes in OKP, the selection principles of OKP interim product production schemes need to be provided, and an evaluation method for multi-criteria decision-making problems in selecting reasonable interim production processes is worth further investigation. Moreover, we also recognize that better approximations than the theoretical simulation method (MLHPP) we may be helpful for implementing the computer-aided simulation of complex production task structures and could be another direction of future research.
CHAPTER 5 ENTROPY-WEIGHTED ANP FUZZY COMPREHENSIVE EVALUATION OF INTERIM PRODUCT PRODUCTION SCHEMES IN OKP

5.1 Introduction

With the development of OKP, which is aimed at managing interim products, establishing specialized production systems, optimizing the technological process, improving the piecewise rate of the unit area and shortening the subsection production cycle are becoming increasingly important. However, due to complicated interim product operation relationships and production processes in OKP, these are complex problems that cannot be precisely described with mathematical models.

As introduced in Chapter 3 and Chapter 4, in OKP, interim products are not only the operation units of production but also the components of the work task decomposition for the final product. They are component parts in the stepwise formation of the final product. The interim products in shipbuilding, for example, include not only sub-segments, parts and components but also an outfitting pallet, module, unit, pipe fitting, etc. Interim product specialization is the production trend of modern OKP.

The essence of modern interim product production in OKP is to establish a flexible production line. The flexible flow shop in large-scale OKP often refers to complex production, e.g., shipbuilding. A top-down refinement method is often used in OKP to specialize the product design and production decomposition in OKP, which also results in complicated interim product operation relationships in OKP. In OKP, based on similar operation characteristics, grouping the various types of interim products and expanding the interim product groups/batches with the same processing method in construction establishes the batch flow shop positioning. This batch process is able to take full advantage of interim product production capacity and simultaneously
reduce the production resource occupancy and repeated use, which thus improves production efficiency and reduces the cost of OKP.

An OKP flexible flow shop is different from flow shops in batch and mass production. The primary reason is that all the products or interim products in an OKP flow shop are different, whereas the ones in the flow shops in batch and mass production are the same for a relatively large number of repetitions. That is, most OKP products are complex-shaped structural components, where there are only few completely identical OKP interim products in the same batch. Therefore, OKP interim product production has the nature of multi-criteria production, and this corresponds to the different manufacturing technologies and methods. The ability to reasonably and efficiently select group/batch production schemes for OKP interim products has important implications for multi-criteria production decisions of OKP enterprises.

The production priority order and process correlations of various types of interim products (such as parts, components and subsections) form a variety of OKP interim product process routes. Based on the process routes of the OKP interim products, our research evaluates different interim product’s production schemes in OKP and provides decision support for OKP enterprises to make full use of production resources to realize the highest level of efficiency.

The rest of this chapter is organized as follows: Section 5.2 presents the introduction of related research background. Section 5.3 describes the multi-criteria decision-making problem and characteristics of OKP interim product production. Section 5.4 introduces the selection principles of OKP interim product production schemes. Section 5.5 presents entropy-weighted ANP fuzzy comprehensive evaluation of interim product production schemes in OKP. Section 5.6 gives the results from case studies in a shipbuilding company. Finally, Section 5.7 draws conclusions and proposes future research.
To our best knowledge, there are a relatively small number of references that discuss to a meaningful extent the optimization of OKP interim product production schemes. Even within this small number of references, the schemes are either loosely mentioned or are indirectly related to our research. For most OKP enterprises, the primary problem of the current multi-criteria evaluation method is how to determine the scale of a judgement matrix (i.e. provide a scale for measuring intangibles and method of establishing priorities when determining the relative importance of different attributes with respect to the goal or objective) and determine the weight set (Kong et al. 2006); currently, the method primarily depends on the rich experience of relevant specialists. These subjective decisions make the evaluation results prone to disagreements. Assessing the production schemes of interim products in OKP is similar to evaluating projects. For judging and optimizing interim product production schemes in OKP, the selection principles of OKP interim product production schemes should be provided, and an evaluation method based on entropy-weighted ANP fuzzy comprehensive evaluation is presented in this work.

5.2 Research background

In this section, fuzzy comprehensive evaluation method, entropy and ANP will be introduced.

5.2.1 Fuzzy comprehensive evaluation

According to the introduction of Xi et al. (2013), fuzzy comprehensive evaluation method is a synthetical assessment method that applies fuzzy mathematical principles to evaluate things and phenomenon affected by variety of factors. It regards evaluation objectives as a fuzzy set (named the Factor Set $U$ ) composed of variety of factors with different assessment levels selected.
Another fuzzy set named the Evaluation Set $V$ is employed to calculate the membership degree of each individual factor in the Evaluation Set to establish a fuzzy matrix. The quantitative evaluation value of each factor is finally determined by calculating the weight distribution of each factor in evaluation goal. It applies the fuzzy transformation theory and maximum membership degree law, and makes a comprehensive evaluation to various factors. Specific steps are as follows (Xi et al. 2013):

1. Determine the Factor Set of evaluation object, that is $U = \{ u_1, u_2, \ldots, u_m \}$. It is a set composed of $m$ kinds of evaluation factors.

2. Determine the Evaluation Set, that is $V = \{ v_1, v_2, \ldots, v_n \}$. It’s a set composed of $n$ kinds of evaluation standards.

3. Construct single-factor evaluation matrix. Evaluate single-factor and then get vector $R_i$. A single-factor evaluation matrix $R$ is constituted by numbers of single-factor evaluation vector put together. There are some commonly used membership degree calculation function of single-factor, such as "linearity lower semi-ladder-shaped" distribution function and so on.

$$
R = \begin{bmatrix}
R_1 \\
R_2 \\
\vdots \\
R_m \\
\end{bmatrix} = \begin{bmatrix}
r_{11} & r_{12} & \cdots & r_{1n} \\
r_{21} & r_{22} & \cdots & r_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
r_{m1} & r_{m2} & \cdots & r_{mn} \\
\end{bmatrix}
$$

(5-1)

In (5-1), $R$ is a fuzzy relationship matrix composed of evaluation Factor Set $U$ and the Evaluation Set $V$.

4. Determine evaluation factors weight vector $E = \{ e_1, e_2, \ldots, e_m \}$.
Comprehensive evaluation. The last results of comprehensive evaluation can be got by doing complex operations calculation between single factor weight vector $E$ and fuzzy relationship matrix $R$, which is as follows.

$$B = E \times R = \{b_1, b_2, \ldots, b_m\}$$

(5-2)

In (5-2), $b_i$ is the membership degree value of evaluation samples to each evaluation standard. The determination results are usually defined according to the maximum membership degree law.

5.2.2 Entropy

In thermodynamics, as introduced by Wikipedia, entropy is a measure of the number of specific ways in which a thermodynamic system may be arranged, commonly understood as a measure of disorder: According to the second law of thermodynamics the entropy of an isolated system never decreases; such a system will spontaneously proceed towards thermodynamic equilibrium, the configuration with maximum entropy. Systems that are not isolated may decrease in entropy, provided they increase the entropy of their environment by at least that same amount. Since entropy is a state function, the change in the entropy of a system is the same for any process that goes from a given initial state to a given final state, whether the process is reversible or irreversible. However, irreversible processes increase the combined entropy of the system and its environment. The change in entropy of a system was originally defined for a thermodynamically reversible process as $\Delta S = \int \frac{dQ_{rev}}{T}$, where $T$ is the absolute temperature of the system, dividing an incremental reversible transfer of heat into that system ($dQ$). (If heat is transferred out the
sign would be reversed giving a decrease in entropy of the system.) The above definition is sometimes called the macroscopic definition of entropy because it can be used without regard to any microscopic description of the contents of a system. The concept of entropy has been found to be generally useful and has several other formulations. Entropy was discovered when it was noticed to be a quantity that behaves as a function of state, as a consequence of the second law of thermodynamics. In the modern microscopic interpretation of entropy in statistical mechanics, entropy is the amount of additional information needed to specify the exact physical state of a system, given its thermodynamic specification. Understanding the role of thermodynamic entropy in various processes requires an understanding of how and why that information changes as the system evolves from its initial to its final condition. It is often said that entropy is an expression of the disorder, or randomness of a system, or of our lack of information about it. The second law is now often seen as an expression of the fundamental postulate of statistical mechanics through the modern definition of entropy.

5.2.3 Analytic network process (ANP)

Saaty (1996) considered the dependences and feedback of the elements, and then developed the analytic network process (ANP). So the network spreads out in all directions and its cluster of elements are not arranged in a particular order (Saaty, 2004). Zhu et al. (2015) describe the ANP as follows: in multi-criteria decision making, the analytic hierarchy process (AHP) (Saaty, 1980) is a popular methodology to derive priorities of compared elements (or objectives, alternatives etc.) to assist decision makers (DMs) to make decisions. It has been successfully applied in practice (Saaty, 1989, 2008). The AHP has a limitation that it cannot deal with interactions and dependencies between the elements in the levels of the hierarchy. For example, to predict the
market share of cell-phone providers, the elements that influence the market share of a company can be costs and services, where the services may also influence the costs. ANP overcomes this limitation. In the ANP, the network allows clusters of elements influence each other, or has loops if the elements in the clusters have inner dependences. With the advantage in dealing with dependences and feedback, ANP is very useful in many practical applications such as the interdependent information system project selection (Lee et al., 2000), the R&D project selection (Meade et al., 2002), the logistics service provider selection (Jharkharia et al., 2007), the product mix planning (Chung et al., 2005), the SWOT analysis (Yüksel et al., 2007), the financial-crisis forecasting (Niemira et al., 2004), and the multi-criteria analysis (Wolfslehner et al., 2005).

5.3 The multi-criteria decision-making problem and characteristics of interim product production in OKP

Interim products are prefabricated parts that are between the final product and raw materials when the entire OKP project is decomposed. Using shipbuilding as an example, hull parts, hull components, outfitting units, outfitting pallet and hull blocks are the interim products of a certain level in a production decomposition structure (PPS).

Manufacturing interim products in OKP requires collaborative production of different departments and processes. Production schemes with different process combinations are formulated under the joint participation of different decision makers (product design department, production department and production technology department), and each department cooperates in production according to its own objective. It makes the production scheme selection of interim products in OKP a multi-criteria decision-making problem that has the following characteristics:
1. Multiple criteria of the decision-making problem (e.g., production time, production cost and workforce allocation etc.)

2. The criteria of the multi-criteria decision-making problem are not comparable, which means there is not a unified measurement standard or units of measurement for multiple criteria.

3. There are conflicts among multiple criteria. One production scheme, which can improve a certain criteria value, may lead to the deterioration of another target value.

5.4 Principles for selecting OKP interim product production schemes

OKP interim product production schemes refer to the method of producing OKP interim products, which includes the interim product group/batch division, and the interim product group/batch production method. The interim product is the “unit” of the one-of-kind production. Shipbuilding is used as an example: with the continuous change of modern shipbuilding conditions, the interim product outfitting process and contents, outfitting technologies and related production organizing method, etc., in various production stages and links become the factors that influence production schemes. According to the description by Huang et al. (2013), the selection principles of OKP interim product production schemes are indicated in the following Section 5.4.1 and Section 5.4.2.

5.4.1 General requirements for an interim product production scheme

OKP interim product production schemes have a powerful influence on the OKP quality, cost and construction cycle. Therefore, when designing the entire OKP plan, selecting a reasonable
interim product production scheme is an extremely important link. It is also one of the technical decisions of organizing production in OKP.

The general requirements for an interim product production scheme are the following:

1. To adapt to the specific requirements in OKP and to make full use of existing equipment and venues;
2. To ensure the completion of the annual or periodic OKP production plan;
3. To meet the requirements of the interim product structure and process;
4. To obtain the best technical and economic metrics, such as ensuring quality, shortening production cycle, improving production efficiency, etc.;
5. To contribute to the reasonable organization of labor and balancing time;
6. To contribute to improve construction conditions and reducing labor intensity;
7. To contribute to expand mechanization and automation production;
8. To rationally utilize the new technology and modern management method to improve the level in the field of OKP construction.

5.4.2 Primary factors considered in selecting the interim product production scheme

Primary factors considered in selecting the interim product production scheme are as follows:

1. Production capacity in OKP. Using shipbuilding as an example, the shipyard production capacity includes processing capacity of the hull workshop and outfitting workshop, hoisting transportation capacity of the ship-building berth and workshop, and production area of the assembly welding workshop (Huang et al. 2013). Among them, the transportation capacity is the key factor that affects the building scheme.
The selection of the building method for large components and hull segmentations on the building berth largely depends on the lifting capacity of the building berth.

2. General layout of the production site in OKP. In shipbuilding, the layout includes the number and size of the building berth and dock, area of the storage yard, plane processing and molding bed, infield welding zone, area of the infield and outfield, etc. (Huang et al. 2013).

3. The labor requirement and labor organization forms in OKP. This determines the equilibrium assignment of the labor requirement and the coordination of various types of work.

4. The situation of collaboration with other enterprises. In recent years, the rational division of labor in OKP can greatly improve the production strength of the main factory and reduce the cost of operation. Partial interim product production should be outsourced.

5. Technological transformation planning in OKP.

6. Batch size of OKP interim products: Although the similarities of the interim product family can be controlled, it is restricted to the actual production capacity. Selection of the product batch size is the premise for rational OKP interim product production. How to control the batch production according to the schedule becomes one of the factors considered in OKP.
5.5 Entropy-weighted ANP fuzzy comprehensive evaluation of interim product’s production schemes in OKP

As we can see from the above principles, the factors to be considered in OKP interim product production are complicated. Therefore, with the purpose of obtaining the most reasonable production scheme in terms of technology and economy, the OKP interim product batch division and production scheme selection should be comprehensively analyzed according to the production condition, building technology, product structure features, etc. Because multiple factors have different degrees of influence on the interim product batch division and production schemes, and the information in evaluating production schemes/processes is generally fuzzy and incomplete, it is necessary to use a fuzzy comprehensive evaluation method to accurately reflect the synergies. However, for solving multi-criteria decision-making problems in OKP, how to judge the matrix scale and determine the weight set, which is the primary problem in fuzzy comprehensive evaluation, still depends on the rich experience of relevant specialists. The subjectivity makes the evaluation results prone to disagreements. The related research on solving the problem in OKP process assessment is still relatively limited. This work combines objective and subjective weights based on entropy and ANP to comprehensively and scientifically evaluate the interim product batch division and production schemes in OKP. The proposed method is easy to operate, and the improved fuzzy comprehensive evaluation can provide multi-criteria decision-making support for OKP interim product production.

5.5.1 Combination weighting approach based on entropy and ANP

The Entropy method is a methodology that determines weights according to the degree of information reliability that various indices reflect. Therefore, entropy weight is characterized by
data objectivity. The analytic network process (ANP) is an evaluation methodology that determines index weights based on subjective judgment. In traditional evaluation methods, e.g. radix evaluation method, grey relational analysis, ANP/AHP and fuzzy evaluation method, it is difficult to determine the weight of indices and there is a lot of subjectivity and thoughtlessness. We adopt a linear combination weighting approach based on entropy and ANP to achieve the unity of objectivity and subjectivity. This method can not only fully retain the information that each index value transmits but also can modify the index weights through the knowledge and experience of specialists.

5.5.1.1 Target attribute weight based on entropy

The concept of entropy is derived from thermodynamics and is a measurement of the uncertainty of the system. The entropy method determines the weights according to the amount of information reflected by the degree of variation of the evaluation index values. The multi-criteria attributes that are used in evaluating the interim product production schemes are unable to determine the amount of information. In other words, the information quantity is uncertain. The more information an objective attribute contains, the greater the influence the index will have on the evaluation of the production scheme. The system may be in different states, where the probability of each state is \( p_i (i = 1..n) \), and the system entropy is defined as follows (Dai et al. 2010):

\[
E = -k \sum_{i=1}^{n} p_i \ln p_i , \quad 0 \leq p_i \leq 1; \quad \sum_{i=1}^{n} p_i = 1, k = 1/\ln n \; \text{and when} \; p_i = 0, \; E = 0. \quad (5-3)
\]

The calculation method for the index weight can include the subjective weighting method and the objective weighting method. We adopt the entropy method to determine the weights of
the evaluation indices and it is an objective weighting method. The weight determination of indices is as follows:

Step 1: After the normalization processing of the objective attribute matrix, define the weight value of the \( j \) th attribute of the result matrix:

\[
E_j = -k \sum_{i=1}^{m} \frac{r_{ij}}{r_j} \ln \frac{r_{ij}}{r_j}
\]  

(5-4)

Here, \( r_j = \sum_{i=1}^{m} r_{ij}, j = 1,2,\ldots,n \). Suppose if \( r_{ij} = 0, E_j = 0 \).

Step 2: Further address the result of Step 1 with normalization processing, and obtain the objective entropy weight of attribute \( j \).

\[
w_j = \left(1 - E_j\right) / \sum_{j=1}^{n} \left(1 - E_j\right)
\]  

(5-5)

Here, \( 0 \leq w_j \leq 1, \sum_{j=1}^{n} w_j = 1 \).

In OKP, the entropy weights are applied in the evaluation, which possesses the following advantages: (1) avoids only being influenced by subjective weights (expert judgment); (2) reveals main factors that affect the construction of OKP interim products and helps objectively establish an evaluation index influence degree system; (3) the evaluation basis depends on evaluation indices’ own data, which combines qualitative analysis with quantitative analysis and makes evaluation results more scientific; (4) from the aspect of computation, it avoids the level-by-level refinement of evaluation indices in traditional fuzzy comprehensive evaluation methods for selecting OKP interim product production schemes, which significantly decreases the computing load and enhances the evaluation method practicality.
The index weight determined by the entropy method is entirely based on the relationship among the data. However, the objective weight value occasionally differs greatly from reality. ANP allows experts or decision makers to consider the interaction of various elements in a complex dynamic system; thus, it is more similar to the actual situation. Therefore, we believe that the weight should be the comprehensive measurement that considers both expert judgment (subjective weight of an ANP) and an entropy weight.

5.5.1.2 Target attribute weight based on ANP

The analytic network process (ANP) is a decision-finding method. ANP can model complex decision problems, where a hierarchical model is not sufficient. ANP allows for feedback connections and loops. Generally, ANP is the method used for solving unstructured and semi-structured decision problems in a social economic system. ANP has been applied to government affairs, military applications, commercial production and many other fields and has gained comprehensive attention. For example, ANP has been presented as a potentially valuable method to support the selection of projects, such as R&D project selection (Meade et al. 2002) and green supplier evaluation (Büyüközkan et al. 2012). In OKP, the structure of a decision problem in the production of interim products is a network. Structuring complex problems well and considering multiple criteria has the potential to lead to more informed and better decisions. This is a novel attempt to use fuzzy comprehensive evaluation based on ANP weight in production scheme optimization, which to a certain extent, enriches process optimization methods in manufacturing.

The weight determination of indices is as the follows:
Step 1: Build the super matrix. Elements \( p_s(s=1,\ldots,n) \) are in the control layer. Under the control layer, there are element groups \( C_1,\ldots,C_N \) in the network layer. \( C_i \) contains elements \( e_{i_1},\ldots,e_{i_n} \), \( i=1,\ldots,N \). According to the criterion of the control layer element \( p_s(s=1,\ldots,n) \), take element \( e_{jl}(l=1,2,\ldots,n_j) \) of \( C_j \) as the sub-criterion, and make a comparison of the indirect predominance degree according to the influence of elements \( e_{i_m} \) on \( e_{jl} \). Elements \( e_{i_m} \) belong to element group \( C_i \). The super matrix is built as the follows:

\[
W = \begin{bmatrix}
W_{11} & W_{12} & \cdots & W_{1N} \\
W_{21} & W_{22} & \cdots & W_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
W_{N1} & W_{N2} & \cdots & W_{NN}
\end{bmatrix}
\] (5-6)

Here, elements \( e_{i_1},e_{i_2},\ldots,e_{i_n} \) in \( C_i \) affect \( e_{j_1},e_{j_2},\ldots,e_{j_n} \) in \( C_j \). The column vector of sub-block \( W_{ij} \) in the super matrix is the priority vector of the influence degree.

Step 2: Build the weighting matrix. Take \( p_s \) as the criterion. Compare the importance degree of each group’s elements under \( p_s \) for \( C_j(j=1,\ldots,N) \). The sorting vector components, which correspond to the element groups that are not related to \( C_j \), are equal to zero. Then, the weighting matrix \( A \) can be built as the follows:

\[
A = \begin{bmatrix}
a_{i_1} & \cdots & a_{i_N} \\
\vdots & \vdots & \vdots \\
a_{N_1} & \cdots & a_{NN}
\end{bmatrix}
\] (5-7)
Step 3: Construction of weighting super matrix. The elements in the super matrix are weighted; then, \( \mathbf{W} = (\mathbf{W}_{ij}) \) can be obtained. Here, \( \mathbf{W}_{ij} = a_{ij} \mathbf{W}_{ij} \), \( i = 1, \cdots, N \), \( j = 1, \cdots, N \). \( \mathbf{W} \) is the weighting super matrix, where the column sum is 1.

\[ \mathbf{W} = (\mathbf{W}_{ij}) \text{ is the super matrix. } \mathbf{A} = (a_{ij}) \text{ is the weighting matrix. } \mathbf{W} \text{ is the weighting super matrix.} \]

5.5.2 *Fuzzy comprehensive evaluation model based on entropy and ANP*

The model is the following:

1. Set \( n \) elements of the multi-criteria decision-making problem: \( H_1, H_2, \cdots, H_n \), and there are \( m \) decision schemes: \( D_1, D_2, \cdots, D_m \). Under the influence of factor \( H_j (j = 1, 2, \cdots, n) \), the attribute value of the decision scheme \( D_i (i = 1, 2, \cdots, m) \) is \( x_{ij} \).

The evaluation matrix of \( n \) index factors in \( m \) schemes is as follows:

\[
\mathbf{A} = \begin{bmatrix}
  x_{11} & x_{12} & \cdots & x_{1n} \\
  x_{21} & x_{22} & \cdots & x_{2n} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]  \hspace{1cm} (5-8)

2. Because each evaluation attribute unit, dimension and magnitude are different, it is necessary to make a standardized treatment for each index of the decision matrix. This work adopts the gauge transformation method to obtain the fuzzy evaluation matrix \( \mathbf{R} \):

\[
r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \quad \forall i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n
\]  \hspace{1cm} (5-9)
3. Comprehensive measurement. To reflect the importance of evaluation indices, set the subjective weight provided by ANP to $w_j$. Based on the above entropy weight $w_j$ (Section 5.5.1) and ANP weight $w_j$ (Section 5.5.1), obtain the objective attribute final weight $W_j (j = 1, \cdots, n)$.

$$W_j = w_j \cdot w_j / \sum_{j=1}^{n} w_j \cdot w_j \quad j = 1, \cdots n \quad (5-10)$$

4. Establish comprehensive fuzzy evaluation models. With the fuzzy evaluation matrix and comprehensive weight vector, using fuzzy mathematics theory, we can obtain the following comprehensive fuzzy evaluation model:

$$Z_{ij} = W_j r_{ij} \quad (5-11)$$

Because $W_j$ has been normalized, the composition of the fuzzy relation can use ordinary real number addition and multiplication operations:

$$z_i = \sum_{j=1}^{n} W_j \cdot r_{ij} \quad z_i \in [0,1], j = 1,2,\cdots,n \quad (5-12)$$

Here, $z$ is the quality value vector of the estimated scheme. This work adopts the maximum membership degree method for evaluation. The larger the value of $z_i$, the larger the comprehensive benefit of the evaluated scheme, which means we can establish a comprehensive ranking of the evaluation schemes according to $z_1, z_2, \cdots, z_m$. 
5.6  Case study

Shipbuilding is a typical large-scale OKP. The hull block is the final assembly of the interim products in shipbuilding. Various types of components and parts are assembled to form the hull blocks. The hull blocks are then combined on the ship-building berth to form the overall ship. Therefore, research on the production of hull blocks is a typical OKP. We use the hull block division and assembly as research objects.

5.6.1  Problem analysis of the hull block division and assembly

Dimensions, shapes, weights and division positions of the hull blocks greatly influence the shipbuilding cycle time, cost and quality. There are many factors to be considered when dividing and assembling hull blocks in shipbuilding. Dividing hull blocks should comprehensively consider multiple factors, such as the production conditions, shipbuilding technology and the features of hull structure, to obtain the most reasonable division scheme in terms of technology and economy.

5.6.2  Principles for the hull block division and assembly

Based on the description by Huang et al. (2013), considering aspects of structure characteristics and strength are indicated as follows:

1. The circumferential joint should not be located at the stress positions of the hull total strength or the local strength, such as the midship, hull girder section break and the midpoint of each rib spacing.
2. The structural stress concentration region should avoid being located at the hull block joint.
3. The divided hull blocks should have an adequate rigidity.

4. The hull block joint should possibly be located at the connection part of the structure’s original slab or node (such as the elbow board).

Based on the description by Huang et al. (2013), considering aspects of technology and construction conditions are indicated as follows:

1. The hull block division scheme should be based on the steel plate size (length and width, though the primary factor is the length) to reduce the docking splicing seams and improve the steel usage rate.

2. The shipyard painting shed size should be considered. The hull block outline dimension cannot be larger than the shed size.

3. Generally, weight is also an extremely important consideration factor. When determining the hull block weight, the maximum lifting weight, temporary strengthening weight of the hull blocks and the preassembly degree of the hull block should be considered comprehensively.

4. The end joint of the bottom, side shell and deck should be located in the same cross-section to form a neat annular seam, which can simplify the installation processes. Meanwhile, to avoid a local stress concentration zone, the structure characteristics and strength should be taken into consideration.

5. Sectional division should be conducive to maximize the use of automatic and semi-automatic welding. Thus, the segment size of the hull parallel middle body and straight part can be slightly larger. The head segments and rear segments that have larger curved surfaces can be slightly smaller or can be appropriately vertically divided.
6. The decision of the block joint position should be advantageous for the ship precast and pre-assembly. The decision should consider the adjacent block installation parts' layout and the coordination of outfitting units and structures in the hull blocks. For example, the division of the engine and pump room area block and engine room bottom block should fully consider the installation requirements of the host to ensure that the host can be perfectly placed in one block; the division of the engine room block should take the integrity of the central control room unit into consideration; the division of the ship head block should consider the mooring equipment integrity, etc. Moreover, the patching work should be reduced as much as possible, such as the work for the seams of pipe joints, and ensure that the block can be in a condition to perform a tightness test.

7. If the ship bottom structure belongs to the longitudinal framework type, the vertical division can be used, and the division of the ship bottom block should be near the center girder. However, the transverse system structure is not suitable to make the vertical division because it reduces the workload of the docking.

5.6.3 Case description

This work evaluates the four assembly processes of a double-bottom hull block. Kong et al. (2006) briefly introduced seven production schemes for the typical double-bottom hull block assembly, and the assembly processes $A, B, C, D$ are described in the following:

Building Scheme $A$: Automatically weld jointed boards in the inner bottom ($N$), and then assemble the inner bottom longitudinal frame. After assembly, hang the ribbed slabs, and then weld the longitudinal frame and inner bottom, ribbed slabs and the inner bottom and ribbed
slabs and longitudinal frame. After welding, turn over the welded framework, and place outer bottom plate $B$ on it (outer bottom plate was first joined together and then automatically welded; also, the longitudinal frame was already assembled.). The welding of the outer bottom and frame structure is finally processed.

Building Scheme $B$: Automatically weld jointed boards in the inner bottom ($N$), and then assemble and weld the inner bottom longitudinal frame. After assembly, hang the ribbed slabs, and then weld the longitudinal frame and inner bottom, ribbed slabs and inner bottom, and ribbed slabs and longitudinal frame. After welding, hang and assemble the outer bottom longitudinal frame, and then place the outer bottom plate $B$ on it (the outer bottom plate was first joined together and then automatically welded.). Moreover, turn over the entire hull block. Finally, weld the outer bottom plate, outer bottom longitudinal frame and the ribbed slabs.

Building Scheme $C$: Automatically weld jointed boards in the inner bottom ($N$), and then assemble and weld the inner bottom longitudinal frame. The outer bottom plate $B$ was joined together and automatically welded. Afterwards, assemble the outer bottom longitudinal frame, and weld the longitudinal frame. Moreover, assemble and weld the ribbed slabs on the inner bottom plate. After welding, turn over the welded frame; place the outer bottom plate on it and weld them.

Building Scheme $D$: Automatically weld the jointed boards in the outer bottom plate $B$. Then, automatically weld jointed boards in the inner bottom ($N$). In addition, assemble and weld the inner bottom longitudinal frame. Next, assemble and weld the ribbed slabs on the inner bottom plate. Afterwards, place the construction of the outer bottom plate and longitudinal frame on the formed frame, and assemble them. Finally, turn over the hull block, and then weld the components that are related to the outer bottom plate.
5.6.4 Selection of evaluation indices

We select four first-level evaluation indices that include quality satisfaction, automation degree, welding efficiency, and cost rationality for evaluation. The two-level evaluation index system’s concrete numerical values are indicated in the following Table 5-1 (Kong et al. 2006). The data were decided through expert investigation and based on each assembling scheme’s single factor membership degree.

Table 5-1. Multi-attribute index data of four hull block building schemes

<table>
<thead>
<tr>
<th>Evaluation Indices</th>
<th>Evaluation Schemes</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quality Satisfaction</td>
<td>Simplify the operation precision</td>
<td>1.0</td>
<td>0.8</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td>(1) 0.25</td>
<td>(1-1) 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Meet the requirements of classification society</td>
<td>1.0</td>
<td>0.8</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>(1-2) 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Automation Degree</td>
<td>Adjustment ability</td>
<td>0.8</td>
<td>1.0</td>
<td>0.8</td>
<td>0.4</td>
</tr>
<tr>
<td>(2) 0.25</td>
<td>(2-1) 0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Utilization rate of automation equipment</td>
<td>1.0</td>
<td>0.8</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>(2-2) 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Automation degree</td>
<td>1.0</td>
<td>0.8</td>
<td>0.4</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>(2-3) 0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5-1. Multi-attribute index data of four hull block building schemes (continued)

<table>
<thead>
<tr>
<th>Evaluation Indices</th>
<th>Evaluation Schemes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
</tr>
<tr>
<td>Welding Efficiency</td>
<td>(3)0.30</td>
</tr>
<tr>
<td>operating ratio of</td>
<td></td>
</tr>
<tr>
<td>down-hand welding</td>
<td>(3-1) 0.33</td>
</tr>
<tr>
<td>Number of turning</td>
<td></td>
</tr>
<tr>
<td>overs</td>
<td>(3-2) 0.33</td>
</tr>
<tr>
<td>Auxiliary measures</td>
<td></td>
</tr>
<tr>
<td>(3-3) 0.17</td>
<td></td>
</tr>
<tr>
<td>Difficulty of</td>
<td></td>
</tr>
<tr>
<td>assembling structure</td>
<td></td>
</tr>
<tr>
<td>(3-4) 0.17</td>
<td></td>
</tr>
<tr>
<td>Cost Rationality</td>
<td>(4)0.20</td>
</tr>
<tr>
<td>Expenditure of time</td>
<td></td>
</tr>
<tr>
<td>(4-1) 0.34</td>
<td></td>
</tr>
<tr>
<td>Number of workers</td>
<td></td>
</tr>
<tr>
<td>(4-2) 0.33</td>
<td></td>
</tr>
<tr>
<td>Rate of the existing</td>
<td></td>
</tr>
<tr>
<td>equipment utilization</td>
<td></td>
</tr>
<tr>
<td>(4-3) 0.33</td>
<td></td>
</tr>
</tbody>
</table>

In the selection of OKP interim product production processes, most evaluation information is incomplete and fuzzy. In Table 5-1, based on the practical production of interim products in shipbuilding, five assessment grades can be determined (Kong et al. 2006): excellent ($v_1$), good ($v_2$), average ($v_3$), bad ($v_4$), very bad ($v_5$). $V = \{v_1, v_2, v_3, v_4, v_5\}$; for each $v_i \in V, (i = 1, 2, 3, 4, 5)$, set the corresponding grade values: 1.0, 0.8, 0.6, 0.4, 0.2, i.e. $V' = \{1.0, 0.8, 0.6, 0.4, 0.2\}$. 

100
The ANP network is as follows:

Figure 5-1. The ANP network

5.6.5 Computing process

There are 4 steps in the computing process.

Step 1: According to the data in Table 5-1, we construct and normalize the evaluation index matrix $R$:

$$
A = \begin{bmatrix}
1 & 0.8 & 0.4 & 0.2 \\
1 & 0.8 & 0.6 & 0.4 \\
0.8 & 1 & 0.8 & 0.4 \\
1 & 0.8 & 0.4 & 0.2 \\
1 & 0.8 & 0.4 & 0.2 \\
0.8 & 1 & 0.8 & 0.4 \\
0.4 & 0.1 & 0.8 \\
0.4 & 0.1 & 0.8 \\
0.4 & 0.1 & 0.8 \\
1 & 0.8 & 0.6 & 0.4 \\
0.2 & 0.4 & 1 & 0.6 \\
1 & 0.8 & 0.6 & 0
\end{bmatrix}
^T
$$

Normalization processing

$$
R = \begin{bmatrix}
0.366 & 0.303 & 0.153 & 0.125 \\
0.366 & 0.303 & 0.229 & 0.250 \\
0.293 & 0.379 & 0.306 & 0.250 \\
0.366 & 0.303 & 0.153 & 0.125 \\
0.366 & 0.303 & 0.153 & 0.125 \\
0.293 & 0.379 & 0.306 & 0.250 \\
0.000 & 0.152 & 0.382 & 0.500 \\
0.146 & 0.303 & 0.382 & 0.250 \\
0.000 & 0.152 & 0.382 & 0.500 \\
0.366 & 0.303 & 0.229 & 0.250 \\
0.073 & 0.152 & 0.382 & 0.275 \\
0.366 & 0.303 & 0.229 & 0.000
\end{bmatrix}
^T
$$
Step 2: According to the standard fuzzy evaluation matrix $R$ and (5-4), we can calculate the entropy value of each index. Based on (5-5), each entropy weight is obtained. According to the data of evaluation indices in Table 5-1 and the ANP network in Fig. 5-1, we can establish the ANP structure model that affects the correlations among the evaluation factors and build the weighting super matrix $W$. Based on the weighting super matrix $W$, each evaluation index’s ANP weight is calculated. In this case, we use SuperDecisions software (Creative Decisions Foundation, Pittsburgh, Pennsylvania, U.S.A.) to implement the ANP for the weight computing of indices. The resulting values are shown in Table 5-2.

<table>
<thead>
<tr>
<th>Evaluation Indices</th>
<th>Entropy Value</th>
<th>Entropy Weight</th>
<th>ANP Weight</th>
<th>Comprehensive Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simplify the operation precision</td>
<td>0.5338</td>
<td>0.0885</td>
<td>0.0682</td>
<td>0.0718</td>
</tr>
<tr>
<td>Meet the requirements of classification society</td>
<td>0.6161</td>
<td>0.0729</td>
<td>0.0687</td>
<td>0.0598</td>
</tr>
<tr>
<td>Adjustment ability</td>
<td>0.6412</td>
<td>0.0681</td>
<td>0.0682</td>
<td>0.0550</td>
</tr>
<tr>
<td>Utilization rate of automation equipment</td>
<td>0.5338</td>
<td>0.0885</td>
<td>0.0771</td>
<td>0.0813</td>
</tr>
<tr>
<td>Automation degree</td>
<td>0.6412</td>
<td>0.0681</td>
<td>0.0653</td>
<td>0.0526</td>
</tr>
<tr>
<td>Operating ratio of down-hand welding</td>
<td>0.4868</td>
<td>0.0975</td>
<td>0.0771</td>
<td>0.0897</td>
</tr>
<tr>
<td>Number of turning overs</td>
<td>0.5838</td>
<td>0.0790</td>
<td>0.0653</td>
<td>0.0622</td>
</tr>
<tr>
<td>Auxiliary measures</td>
<td>0.4868</td>
<td>0.0975</td>
<td>0.0796</td>
<td>0.0933</td>
</tr>
<tr>
<td>Difficulty of assembling structure</td>
<td>0.5838</td>
<td>0.0790</td>
<td>0.0964</td>
<td>0.0909</td>
</tr>
<tr>
<td>Expenditure of time</td>
<td>0.4868</td>
<td>0.0975</td>
<td>0.0796</td>
<td>0.0933</td>
</tr>
<tr>
<td>Number of workers</td>
<td>0.6161</td>
<td>0.0729</td>
<td>0.1282</td>
<td>0.1112</td>
</tr>
<tr>
<td>Existing equipment utilization rate</td>
<td>0.5242</td>
<td>0.0904</td>
<td>0.1282</td>
<td>0.1388</td>
</tr>
</tbody>
</table>
Step 3: According to the comprehensive fuzzy evaluation models (5-11) and (5-12), we can obtain the final evaluation index \( Z = (0.2463, 0.2741, 0.2791, 0.2419)^T \). For the first-level index weights, the comparison between the original subjective weights and the improved comprehensive weights is listed in Table 5-3.

Table 5-3. Comparison of the first-level index weights

<table>
<thead>
<tr>
<th>Original subjective weights of the first-level indices</th>
<th>Improved first-level index weights (sum of the second-level index weights)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>0.1316</td>
</tr>
<tr>
<td>0.25</td>
<td>0.1889</td>
</tr>
<tr>
<td>0.30</td>
<td>0.3361</td>
</tr>
<tr>
<td>0.20</td>
<td>0.3433</td>
</tr>
</tbody>
</table>

The evaluation result comparison between the improved method and the traditional fuzzy comprehensive evaluation method is shown in Table 5-4.

Table 5-4. Evaluation result comparison of two methods

<table>
<thead>
<tr>
<th>Evaluation Schemes</th>
<th>The Improved Evaluation Method</th>
<th>Traditional Fuzzy Comprehensive Evaluation Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Final evaluation index ( Z )</td>
<td>Precedence order</td>
</tr>
<tr>
<td>A</td>
<td>0.2463</td>
<td>3</td>
</tr>
<tr>
<td>B</td>
<td>0.2741</td>
<td>2</td>
</tr>
<tr>
<td>C</td>
<td>0.2791</td>
<td>1</td>
</tr>
<tr>
<td>D</td>
<td>0.2419</td>
<td>4</td>
</tr>
</tbody>
</table>
Step 4: Result analysis. For four first-level evaluation indices, the original subjective weight for cost rationality is 0.2 (Table 5-1), which is the minimum. However, there is a certain deviation between this original subjective weight influence and the actual recognition degree of the total man-hours to build the hull block. Through the entropy-weighted ANP fuzzy comprehensive evaluation method, the sum of the three second-level index weights (expenditure of time; number of workers; existing equipment utilization rate) is 0.3433 (Table 5-3), which increases the weight proportion of the cost rationality index and expands the influence of the work time expenditure and the worker number in the hull block building. Based on the adjusted weights and the final evaluation index $Z$, according to the principle of the maximum membership degree method, we can obtain the precedence order of the four assembly schemes of the double-bottom hull block: $C > B > A > D$. Furthermore, we can conclude that Building Scheme $C$ is the best production scheme to build the double-bottom hull block. At present, most ship manufacturing enterprises control shipbuilding by optimizing the number of workers and planning the existing equipment utilization rate to shorten the shipbuilding period. Our calculated result is consistent with this production control and objectively reflects the influence that the total block building time has on the hull block building. It also indirectly reflects the other three first-level indices’ influence degrees. Therefore, our evaluation method overcomes the disadvantages of the over reliance on subjective weights in traditional evaluation methods. In addition, combined with ANP, the improved method, to a certain extent, overcomes the differences that result from the subjective decisions of the weight set in traditional methods. The method is more complete in theory and actually reflects the objective influences that different indices in the hull block building have on each the building scheme.
5.7 Conclusion

Using generic construction features of interim products in OKP, we establish the influence factor system and provide a solution to the multiple-criteria optimization decision in OKP. With the focus on multiple-criteria decision-making problems formed by interim product production in OKP, we present a method that combines subjective and objective weights based on entropy and ANP to comprehensively evaluate interim product production schemes in OKP. From the perspective of comprehensive evaluation theory, the synthesis of subjective and objective weights in assessment is more scientific and complete. As observed from the case analysis, the evaluation is based on all the target attribute data, and also, multiple-criteria optimization evaluation indices are analyzed through the combination of qualitative and quantitative analyses, which makes the calculation results more comprehensive. The entire calculation process is simple, and the solution is suitable for practical application in analogous types of OKPs.

The optimization of the production processes in OKP provides support for further research on the multiple-resource constrained dynamic scheduling problem and analyzing the corresponding logistics model in external block yard production.

2 Chapter 5 is based on the accepted manuscript (Mei et al., 2016, DOI:10.1016/j.cie.2016.08.016. © 2016 This manuscript version is made available under the CC-BY-NC-NC 4.0 license http://creativecommons.org/licenses/by-nc-nd/4.0/).
CHAPTER 6 CONCLUSION AND FUTURE WORK

6.1 Conclusion

In OKP, when a manufacturing project is decomposed into a list of tasks through top-down refinement, some of the work in WBS (work breakdown structure) requires multiple processes with discrete and non-numerical structures. The research presented in this thesis aimed at developing a closed-loop production dynamic control and optimization framework for interim product manufacturing project based on working hours and manpower in OKP. The contributions of this work include:

1. Unit structures of work tasks in WBS and the discrete nested-set DP (dynamic programming) equation for working time optimization and the corresponding workforce allocation in the double-level-nested parallel task structure.
2. Complex process simulation based on the multilevel hierarchical PERT-Petri net and the closed-loop production cost dynamic control and optimization system in OKP.
3. An influence factor system for optimizing interim product production process in OKP and an effective evaluation method.

We placed emphasis on the study of OR (operation research) systems rather than the static OR problems, considering the time domain of OKP, the production relationship between parts and the whole, and complex structures etc. Regarding OKP as a production system incorporating complex production decomposition, product design uncertainties and changes in resource availability, we deal with the problem of finding a control law for it such that a man-hour cost optimality criterion is achieved.
6.2 Future work

To achieve a cost-effective OKP system, our research has mainly focused on the development of a computer-aided and integrated production system, which is able to control the complex flexible production dynamically and produce highly customized products at near the efficiency of mass production. This research work approaches the problem by optimizing the entire integrated supply chain from the point of view of a customer order driving the integrated supply chain business model. This requires the review and redevelopment of conventional production planning and control theory. Therefore, we expect to make a significant contribution to the theory of production planning and control in general and to OKP methodology in particular. Future work includes:

1. For diverse interim product flexible production lines in OKP, more research on the working time optimization problem with the constraints of product composition parameters such as production schemes, workers of various sorts and different types of manufacture equipment is needed.

2. As for the closed-loop dynamic production control system for OKPs, the bottleneck formation mechanism and solution in a sudden inefficient production process is worthy to be further investigated. In addition, we also recognize that better approximations than the theoretical simulation method (MLHPP) we may be helpful for implementing the computer-aided simulation of complex production task structures and could be another direction of future research.

3. The optimization of the production processes in OKP provides support for further research on the multiple-resource constrained dynamic scheduling problem and analyzing the corresponding logistics model in external block yard production.
The long-term goal of future research is to help manufacturing companies, particularly large-scale OKP, improve their production efficiency and customer satisfaction, and reduce their costs and lead-time by advancing OKP planning and control theory.
REFERENCES


Li, W., & Tu, Y. (2012). Adaptive production scheduling and control in one-of-a-kind production: INTECH Open Access Publisher.


APPENDICES: MRCGA SOURCE CODE

- FIT.m

```matlab
function [z,y]=FIT(x,M,W,T)

N=length(T);
S=floor(length(x)/N);
x=(reshape(x',N,S))';
y=zeros(S,N);
for i=1:S
    yi=zeros(1,N);
    xi=x(i,:);
dxi=sum(xi)/M;
ad=sum(yi);
    while ad<M
        mxi=max(xi);
pos=find(xi==mxi);
yi(pos(1))=yi(pos(1))+1;
        xi(pos(1))=xi(pos(1))-dxi;
ad=sum(yi);
    end
    y(i,:)=yi;
end
end
```
%%
sy=W*sum(y,1);
t=zeros(1,N);
for i=1:N
    syi=sy(i);
    if syi==0;
        t(i)=10*sum(T);
    else
        t(i)=T(i)/syi;
    end
end
z=max(t);

- **GAUCP.m**

```
function [BESTX,BESTY,ALLX,ALLY]=GAUCP(K,N,Pm,LB,UB,ucM,ucW,ucT)

M=length(LB);

farm=zeros(M,N);
for i=1:M
    x=unifrnd(LB(i),UB(i),1,N);
    farm(i,:)=x;
end
```

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ALLX=cell(K,1);
ALLY=zeros(K,N);
BESTX=cell(K,1);
BESTY=zeros(K,1);
k=1;

while k<=K

    newfarm=zeros(M,2*N);
    Ser=randperm(N);
    A=farm(:,Ser(1));
    B=farm(:,Ser(2));
    P0=unidrnd(M-1);
    a=[A(1:P0,:);B((P0+1):end,:)];
    b=[B(1:P0,:);A((P0+1):end,:)];
    newfarm(:,2*N-1)=a;
    newfarm(:,2*N)=b;

    for i=1:(N-1)
        A=farm(:,Ser(i));
        B=farm(:,Ser(i+1));
        P0=unidrnd(M-1);

a=[A(1:P0,:);B((P0+1):end,:)];
b=[B(1:P0,:);A((P0+1):end,:)];
newfarm(:,2*i-1)=a;
newfarm(:,2*i)=b;
end

FARM=[farm,newfarm];

SER=randperm(3*N);
FITNESS=zeros(1,3*N);
fitness=zeros(1,N);
for i=1:(3*N)
    Beta=FARM(:,i);
    SE=FIT(Beta',ucM,ucW,ucT);
    FITNESS(i)=SE;
end

for i=1:N
    f1=FITNESS(SER(3*i-2));
    f2=FITNESS(SER(3*i-1));
    f3=FITNESS(SER(3*i));
    if f1<=f2&&f1<=f3
        farm(:,i)=FARM(:,SER(3*i-2));
fitness(:,i)=FITNESS(:,SER(3*i-2));

elseif f2<=f1&&f2<=f3

farm(:,i)=FARM(:,SER(3*i-1));

fitness(:,i)=FITNESS(:,SER(3*i-1));

else

farm(:,i)=FARM(:,SER(3*i));

fitness(:,i)=FITNESS(:,SER(3*i));

end

end

X=farm;
Y=fitness;
ALLX{k}=X;
ALLY(k,:)=Y;
minY=min(Y);
pos=find(Y==minY);
BESTX{k}=X(:,pos(1));
BESTY(k)=minY;

for i=1:N

if Pm>rand&&pos(1)~=i

AA=farm(:,i);
BB=GaussMutation(AA,LB,UB);

end
farm(:,i)=BB;
end
end
disp(k);
k=k+1;
end

BESTY2=BESTY;
BESTX2=BESTX;
for k=1:K
    TempY=BESTY(1:k);
    minTempY=min(TempY);
    posY=find(TempY==minTempY);
    BESTY2(k)=minTempY;
    BESTX2{k}=BESTX{posY(1)};
end
BESTY=BESTY2;
BESTX=BESTX2;
plot(BESTY,'-b');
hold on

ylabel('value of function')
xlabel('iterations')
grid on

- GaussMutation.m

function mx=GaussMutation(x,lb,ub)

L=length(x);
mx=x;
for i=1:L
m=0.5*(lb(i)+ub(i));
v=(ub(i)-lb(i))/6;
q=normrnd(m,sqrt(v));
if q<lb(i)
q=lb(i);
end
if q>ub(i)
q=ub(i);
end
mx(i)=q;
end

- MainSim.m

clc
clear
close all

ucType=3
switch ucType
    case 1%
        ucN=3;
        ucT=[6,6,3];
        ucM=5;
        ucW=3;
        ucS=1;
    case 2
        ucN=8;
        ucT=[8,4,16,10,6,24,8,12];
        ucM=5;
        ucW=3;
        ucS=3;
    case 3
        ucN=10;
        ucT=10+unidrnd(20,1,ucN);
        ucM=15;
        ucW=3;
        ucS=4;
otherwise
    error('ERROR');
    break
end

K=80;
N=100;
Pm=0.3;
LB=zeros(1,ucS*ucN);
UB=ones(1,ucS*ucN);
[BESTX,BESTY,ALLX,ALLY]=GAUCP(K,N,Pm,LB,UB,ucM,ucW,ucT);

x=BESTX{K};
[z,y]=FIT(x',ucM,ucW,ucT);
disp('');
disp(y);
disp('');
disp(z);

for i=1:ucS
    str=['µÚ',num2str(i),"; "];
disp(str);
pos=[1:ucN];
disp([pos;y(i,:)]');
end